Movement Imitation Mechanisms in Robots and Humans

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Abstract

Imitation mechanisms in artificial and biological agents are of great interest mainly for two reasons: from the engineering point of view, they allow the agent to efficiently utilise the knowledge of other agents in its social environment in order to quickly learn how to perform new tasks; from the scientific point of view, these mechanisms are intriguing since they require the integration of information from the visual, memory, and motor systems. This thesis presents a dual-route architecture for movement imitation and considers its plausibility as a computational model of primate movement imitation mechanisms.

The developed architecture consists of two routes, termed *passive* and *active*. The active route tightly couples behaviour perception and generation: in order to perceive a demonstrated behaviour, the motor behaviours already in the imitator's repertoire are utilised. While the demonstration is unfolding, these behaviours are executed on internal forward models, and predictions are generated with respect to what the next state of the demonstrator will be. Behaviours are reinforced based on the accuracy of these predictions. Imitation amounts to selecting the behaviour that performed best, and re-enacting that behaviour. If none of the existing behaviours performs adequately, control is passed to the passive route, which extracts the representative postures that describe the demonstrated behaviour, and imitates it by sequentially going through the extracted postures. Demonstrated behaviours imitated through the passive route form the basis for acquiring new behaviours, which are added to the repertoire available to the active route. A stereo vision robotic head, and a dynamically simulated 13 DoF articulated robot are utilised in order to implement this architecture, illustrate its behavioural characteristics, and investigate its capabilities and limitations. The experiments show the architecture being capable of imitating and learning a variety of head and arm movements, while they highlight its inability to perceive a behaviour that is in the imitator's repertoire, if the behaviour is demonstrated with execution parameters (for example, speed) unattainable by the imitator.

This thesis also proposes this architecture as a computational model of primate movement imitation mechanisms. The behavioural characteristics of the architecture are compared with biological data available on monkey and human imitation mechanisms. The behaviour of the active route correlates favourably with brain activation data, both at the neuronal level (monkey's F5 'mirror neurons'), and at the systems level (human PET and MEP data that demonstrate activation of motor areas during action observation and imagination). The limitations of the architecture that surfaced during the computational experiments lead to testable predictions regarding the behaviour of mirror neurons. The passive route is a computational implementation of an intermodal-matching mechanism, that has been hypothesised to underlie early infant movement imitation (the AIM hypothesis). Destroying the passive route leads to the architecture being unable to imitate any novel behaviours, but retaining its ability to imitate known ones. This characteristic correlates favourably with the symptoms displayed by humans suffering from visuo-imitative apraxia. Finally, dealing with novel vs. known behaviours through separate routes correlates favourably with human brain activation (PET) data which show that the pattern of activation differs according to whether the observed action is meaningful or not to the observer.

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Declaration

I hereby declare that I composed this thesis entirely myself and that it describes my own research.

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Contents

List of Figures

Chapter 1

Introduction

We do not exist alone. Humans and most other animal species live in societies where the behaviour of an individual influences and is influenced by other members of the society. Within societies, an individual learns not only on its own, through classical conditioning and reinforcement, but to a large extent through its conspecifics, by observation and imitation. Species from rats to birds to humans have been observed to turn to their conspecifics for efficient learning of useful knowledge. One of the most important mechanisms for the transmission of this knowledge is imitation.

At the heart of the ability to imitate lies a mechanism which matches perceived external behaviours with equivalent internal behaviours of its own, recruiting information from the perceptual, motor and memory systems. This mechanism has been shown to be present even in newborn infants, which have been observed to imitate the facial gestures of their caretakers. In humans, malfunctions of this mechanism, surfaced as an inability to imitate, have been used as detectors of pathological disorders including autism and some forms of apraxia. This thesis presents a computational model of this mechanism.

1.1 What is the problem this thesis will address?

This thesis describes theoretical and experimental work performed on the design and implementation of an imitation architecture that allows an imitator agent to match visually perceived movements with equivalent movement of its own. To reduce the number of potential solutions, the following constraints were imposed during the design

process:

- The architecture should be general enough to incorporate evidence from psychology, pathology, and neurophysiology on the mechanisms underlying biological imitation, so it can serve as a model of these mechanisms.
- It should be detailed enough to allow implementation on robotic platforms in order to:
  - equip robots with the ability to imitate;
  - investigate its advantages and its limitations through experimentation.

1.2 Why is it an interesting problem?

1.2.1 The engineering perspective

Designing an architecture which equips robots with the ability to imitate will allow the possibility for learning through demonstration. A human demonstrator can show an example of the task and the robot can learn by imitating the human. This will give people unfamiliar with robot programming the ability to teach robots to perform tasks.

1.2.2 The scientific perspective

Research on imitation spans several disciplines including neurophysiology, psychology, psychophysics and pathology. The available data are often found at completely different levels of description, from neural recordings to behavioural data from human neuropathological examinations. Computational modelling has the potential to integrate data from several disciplines in a common platform. The need for very precise descriptions so that mechanisms can be implementable on computational and robotic platforms illuminates gaps in theories, and allows research to focus on filling these gaps. Even more importantly, computational modelling enables the development of predictions, which can be an important tool for directing further experiments.

1.3 The contributions of this thesis

The work described in this thesis offers the following contributions:

- It introduces a distinction between passive and active imitation, to distinguish between approaches where the imitator goes through a "perceive - recognise - reproduce" cycle (passive imitation) and the motor systems are involved only during the "reproduce" phase, and the approaches where the imitator's motor systems are actively involved during the perception process (active imitation).

- It develops a computational architecture inspired by Meltzoff's Active Intermodal Matching mechanism, hypothesised to underlie early infant imitation. The architecture is capable of imitating and acquiring any demonstrated movement that is within the capabilities of the imitator, but its 'passive' characteristics do not correlate well with all the biological data available.

- To overcome the disadvantages of the passive architecture above, a novel, distributed imitation architecture with 'active' properties is developed. The novelty of this architecture lies in that the same motor structures that are responsible for the *generation* of a movement are recruited in order to perform movement *perception*. Imitation becomes an active process: instead of going through a passive "perceive - recognise - reproduce" cycle, the imitator actively generates possible behaviours in parallel, executes them on internal forward models and selects among them based on the quality of the predictions they offer with respect to the states of the on-going demonstration. However the disadvantage of this route is that it is not capable of imitating demonstrated movements not already present in the imitator's repertoire.

- In order to get the best of both worlds, the two architectures above are combined into the final dual-route architecture: known movements are imitated through the active route; if the movement is novel, evident from the fact that all internal behaviours have failed to predict adequately well, control is passed to the passive route which is able to imitate and acquire the demonstrated movement.

- Algorithmic requirements for such mechanisms are made explicit through the

implementation of the designed architectures on robotic platforms, which include a stereo-vision head and a dynamics simulator of a thirteen degrees-of-freedom robot.

- Computational experiments are performed using as a test set movements that, starting from a rest position, achieve the various postures of the International Standard Semaphore Code (appendix A). This set was selected to allow for easy and compact comparison. The experiments demonstrate the ability of the architecture to imitate, as well as acquire, a variety of movements including unknown, partially known, and fully known sequences of movements. They also reveal the inability of the architecture to match demonstrated movements with existing equivalent ones of its own, when they are demonstrated at speeds unattainable by the imitator.

- Finally, the developed architecture is proposed as a model of primate movement imitation mechanisms. A comparison is performed between the characteristics of the architecture and biological data on human and monkey imitation mechanisms. It is shown that they correlate well, thus offering possible explanations for the biological data. Perhaps more importantly, the limitations of the architecture, as revealed by the computational experiments, offer *testable* predictions regarding the behaviour of the biological mechanisms.

1.4 Roadmap

The rest of the thesis is organised as follows:

- **Chapter 2** sets the overall scene by describing related work on imitation in artificial and biological systems. The utility and the mechanisms of imitation are probed further, followed by research on imitation in assembly and mobile robots. The description of animal imitation research is split into two parts: work aimed at detecting the existence of imitation in various animals is only briefly described here, since it is of limited use to the purposes of this thesis; neurophysiological work probing the monkey's imitation mechanisms is described in more detail in chapter 6, where the developed architecture is proposed as a model. Similarly,

research on human movement imitation is distributed across chapters 3 (work with infants) and 6 (work with adults) so that specialised background work is presented close to the theoretical and computational work that it has provided the inspiration for, or is relevant to.

- **Chapter 3** presents the passive imitation architecture developed, inspired by Meltzoff's AIM hypothesis derived from psychological experiments with human infants, which are also described. The architecture is implemented on a stereo-vision robotic head in the context of deferred imitation of human head movements.

- **Chapter 4** presents the active imitation architecture followed by its implementation on a dynamically simulated thirteen DoF robot. Computational experiments investigating the capabilities and limitations of this architecture are also presented, in the context of arm movements.

- **Chapter 5** presents the dual-route imitation architecture, which combines the passive and active architectures that were described in the previous two chapters. This dual-route imitation architecture is put to the test, confirming its abilities to learn simple novel movements, as well as sequences where none, some, or all the parts are known.

- **Chapter 6** brings together data from neurophysiological experiments with monkeys, human brain activation data, and human pathological data, and compares the behavioural characteristics of the architecture with those of the biological systems. The dual-route architecture is proposed as a computational model of primate movement imitation mechanisms, and the explanations and testable predictions that are offered by the model are described.

- Finally, **chapter 7** reiterates the important points of this thesis, and presents some directions for future research.

- **Appendix A** presents the letters of the International Standard Semaphore Code using 'Bouncer', the developed simulated robot. **Appendix B** lists the publications that have resulted from this work.

Chapter 2

Background

2.1 Introduction

In this chapter, the various issues involved with imitation in biological and artificial systems will be examined, and research that has been investigating these issues will be presented. The chapter is organised as follows: first, the issue of the *utility* of imitation, already briefly discussed in the introduction, will be probed further. It will be argued that imitation is useful as a method of cutting down the search space of problems that the agent is trying to solve, that it is capable of teaching the imitator novel approaches to solving a task, and that it has very low requirements on the trainer. Apart from its technical merits, imitation plays an important role in interpersonal relationships: its importance as a means for recognising other agents, their intentions or even emotions will be discussed. Animal research investigating the existence of imitation in biological systems will be also briefly presented. Then, the issue of the *mechanisms* underlying imitation will be probed further: it will be argued that imitation can occur at several different levels of action description, including "basic", "functional" and "abstract" imitation. An analysis of the subtasks that constitute the imitation process will complete the discussion of the theoretical issues. The presentation will then move to technical issues: research on techniques that have been used in order to equip robotic systems with the ability to imitate human or robot demonstrations will be presented.

2.2 On the *utility* of imitation

Learning by imitation has received a lot of interest in the field of artificial agent design since it offers many benefits to the development of the capabilities of the agent (Demiris and Hayes, 1996).

- First of all, it has the potential of cutting down the solution search space for tasks that the agent is trying to solve (Demiris and Hayes, 1996; Schaal, 1997). An agent in isolation can in theory, given sufficient time and operational resources, learn the solution to any task through reinforcement learning (Sutton, 1991), provided that a suitable reinforcement function is also given. However, the presence of another agent, an 'expert' can be utilised by having that expert demonstrating the solution to the learner who would then learn more quickly by imitation. Even if the learner's imitation is imperfect, it will still serve well as a first approximation for a solution. The search space is essentially reduced to an area around this approximation.

- On a related note, learning by imitation can provide agents with novel solutions to tasks that they wouldn't be able to solve by themselves, due for example, to the lack of an appropriate reinforcement function.

- This method of learning has very low requirements on the teacher: for example, it does not require any explicit reward/punishment signals to be computed by the teacher so they can be passed to the learner. The teacher need not interrupt the task execution process to cater for the learner. Of course, it is possible to incorporate teaching signals in this scheme, if for example, the learner makes mistakes during the imitation process, in which case the teacher can intervene to correct these.

Apart from the aforementioned technical benefits that imitation has for artificial agents, it plays an important role in biological agents as well. Since it is an efficient mechanism for the transmission of information, imitation has been seen as an important form of cultural learning (Tomasello et al., 1993). It has also been suggested that a mechanism who matches externally perceived actions with equivalent internal actions provided the

basis for the development of communication skills and language (Arbib and Rizzolatti, 1996; Rizzolatti and Arbib, 1998). In addition to this, its importance in what is termed "theory of mind" has been the topic of intense research; imitation has been seen as an important mechanism for:

- recognising who others are (Meltzoff and Moore, 1994);
- recognising their intentions, emotions, and other internal attributes (Wallbott, 1991).

Meltzoff has argued that "imitation is to understanding people as physical manipulation is to understanding things" (Meltzoff and Moore, 1994, page 96). The argument was brought forward as a result of a series of experiments which demonstrated that infants are capable of, and are actively engaged in imitation from a very early stage. Although these experiments will be described in more detail in the next chapter (where a computational implementation of the proposed mechanism will also be presented), it is interesting to note here that Meltzoff was essentially suggesting that imitation serves the function of probing the identity of people. Experiments (Meltzoff and Moore, 1992) showed that if an experimenter in the past appeared in front of the infant and performed certain (facial) gestures, and appears again, the infant will imitate the gestures that it had previously seen performed by this experimenter, as if it is asking: "is this person in front of me the one that acts in the way I've seen him doing before, or is it a person that simply looks the same?" The infants use imitation to recognise people, following their general strategy of getting to know things in part through acting on them, so they can bring their perceptual and stored representations into register.

Related work has suggested that even recognition of the experimenter's emotions and other internal attributes can occur through imitation. Subjects were recorded (without their knowledge) while they were observing pictures of faces displaying various emotions. Two weeks later, the subjects were asked to observe the videos of themselves observing the pictures and judge which emotions they were observing two weeks earlier. The results showed that the subjects were accurate in their judgement to a degree above chance (Wallbott, 1991), suggesting that humans recruit imitation as a way of inferring the internal states of others.

2.3 Animal research

Given the benefits that imitation has, its not surprising that nature has equipped many species with the capacity to imitate. Anecdotal reports of the imitation abilities of various animals started at the end of last century (see Whiten and Ham, 1993, for a review). More recently, research on imitation in non-human animals has moved in controlled experimental environments, and has taken place along the following two dimensions:

- What is imitation, and how can it be distinguished from the several other forms of social learning?
- Which animals are capable of imitation?

There is wide disagreement in both dimensions above. Imitation has been used as a label for a variety of social phenomena, including ones which could be explained by other simpler processes, such as observational conditioning, social facilitation and instrumental learning, among others (Galef, 1988). Given that the definitions of imitation differ, there is not wide agreement on a methodology for detecting the existence of imitation abilities (Galef, 1988; Heyes and Galef, 1996), and the adequacy of some of the commonly used ones has been brought into question (Gardner, 1997). Experiments with rats (Heyes et al., 1992), parrots (Moore, 1992), octopuses, dolphins (Tayler and Saayman, 1972), monkeys (Strayer, 1976; Visalberghi and Fragaszy, 1990) and chimpanzees (Custance et al., 1995; Whiten and Custance, 1996; Whiten et al., 1996) have all claimed to have shown the capacity of these animals to learn by observation and imitation.

Reviews of the various definitions and of the work in ethological and psychological aspects of social learning include (Whiten and Ham, 1993) and (Galef, 1988). There have also been attempts to develop frameworks which would encompass all kinds of imitation from all different species, for example (Davis, 1973; Mitchell, 1987; Moore, 1996).

However, one of the difficulties the animal imitation research mentioned above has from the viewpoint of robotics is that, while interesting on its own, it does not provide any

algorithmic insight in the mechanisms underlying the animal's imitation skills which can be used as guidelines for computational and robotic implementations. Neurophysiological research more applicable to the work described in this thesis will be further described in chapter 6.

2.4 On the *mechanisms* of imitation

Having addressed the issue of the utility of imitation, the discussion will now move to the mechanisms that underlie imitation, first of all, to the issues of the different levels at which imitation can occur, followed by a discussion on the distinction between learning to imitate and learning by imitation. An analysis of the different subtasks that are involved in imitation will complete this section.

2.4.1 Levels and types of imitation

There are different levels that imitation can occur at, and these levels do not necessarily share the same mechanisms (Demiris and Hayes, 1997). A possible categorisation of imitation acts could be performed along the following three levels:

(A) **Basic imitation** which can be seen as reproduction of the perceived stimulus, for example, imitation of body movements or speech sounds.

(B) **Functional imitation**, for example picking-up an object, moving towards a door, making a sound to scare off a predator, etc. Essentially, in this level, its not the exact stimulus that is being imitated but rather the function or effect that it has.

(C) **Internal state imitation** i.e. imitation not of the external action but of the presumed internal state of the partner (for example, making a sad face when another one is crying, smiling when others laugh). This can also be thought as empathy, or social attunement.

Trying to differentiate between the different types of imitation has been a recurring theme in biological and artificial agent imitation research, and schemes for distinguish-

ing among them have also been suggested by researchers investigating biological and artificial imitation. For example, Mitchell (1987) introduces a framework where five different levels of imitation are distinguished by the processes that "bring about the imitation" (Mitchell, 1987, page 202). Imitation is viewed as a process that moves through developmental stages, starting from first level imitation (or "mimicry") , which is based on fundamental processes such as evolution, selection and morphogenesis, and reaching more high levels, which are based on more abstract processes, for example, fifth level imitation which is based on planning and the awareness of the other agent's awareness of the situation. Byrne and Russon (1999) also argues that imitation can occur at different levels and they distinguish between action-level and program-level imitation: action-level imitation is viewed as the imitation of basic elements of behaviour, either alone, or in sequential strings, while program-level imitation is viewed as the imitation of the organisational structure at any higher level, in a sense the "strategy" that the demonstrator is adopting. Nehaniv and Dautenhahn (1998) also utilise this distinction between program- and action-level imitation but also introduce a level similar to what was termed as functional imitation earlier on: "effect-level" imitation, which pays special attention to the "form-filling" aspect of imitation, in which the effects on the environment rather than particular motions are to be imitated (Nehaniv and Dautenhahn, 1998, page 65). Similarly, (Miyamoto et al., 1996; Schaal, 1999) point out that there are several strategies for imitation in artificial systems, starting from "indiscriminate intrinsic imitation", where the position and (if available) the force trajectories are to be reproduced in intrinsic space, e.g. joint space, to a strategy that focuses on understanding the task goal of the demonstrator.

2.4.2 Learning to imitate vs. learning by imitation

When the term 'imitation' is used in animal research, it is frequently associated, at least implicitly, with the term 'learning', but it is not immediately clear what the interplay between the two terms is. The distinction that is drawn here postulates that there are two forms of imitation learning: learning to imitate and learning by imitation. In the first one, the agent observes a demonstration and its actions are directed towards finding how to imitate the observed behaviour. Any learning that

is involved revolves around this search for the appropriate motor commands, i.e. the imitation mechanism itself is being learned. On the other side, in learning by imitation, the imitation mechanism is already developed and the agent uses this mechanism in order to develop further skills, usually what is an appropriate action to perform in a particular environmental (and social) situation. The problem is moved from how to imitate, to what and when.

2.4.3 The subtasks of imitation

Having established that imitation is a useful skill to have, and one with many occurrences in nature, it would be useful at this point to try to analyse the individual subtasks that are involved in imitation. The purpose behind this is twofold: it constructs a framework which will assist in evaluating the robotics, computational and animal work that will presented next, and it allows for pinpointing later the areas where the contributions of this thesis reside.

The tasks will be presented in the order in which they would need to be addressed if an agent is introduced to a new environment (by birth, or by transfer) containing other agents. For the newcomer, the task of utilising imitation to its benefit has to proceed through the solution of the subtasks below.

Picking the right agent to imitate

This is a difficult subtask since not all agents are suitable to be imitated, which can be due to two reasons: their design or their behaviour. First of all, they might be unsuitable due to their design, i.e. their physical characteristics and capabilities might be incompatible with the imitator's, potentially rendering imitation impossible. They can also be unsuitable due to their behaviour, since what is good for the demonstrator might not be good for the imitator. Even after rejecting the unsuitable ones, there might be more than one suitable agent left, and a technique for picking one up among the available ones is not clear[1].

[1] Humans and animals, by virtue of living in hierarchical societies, frequently utilise external factors displaying the position of an individual in a society (signs of richness, beauty or strength), or emotional attachment with the demonstrator.

Identifying a beneficial behaviour to imitate

Having picked up a teacher, and assuming that both its physical and behavioural characteristics make imitation possible and useful, the imitator is faced with the subtask of extracting the beneficial behaviour from the stream of data that results from observing the teacher. There are both temporal and attentional segmentation issues: on the temporal side of the segmentation, the beginning and the end of the beneficial behaviour have to be determined, while on the attentional side, it should be determined which aspects of the observed behaviour resulted in the benefits that this behaviour carries. It is not clear yet how people focus their attention during observation with intent to imitate, although steps towards illuminating this mechanism have been taken: Mataric and Pomplun (1998) have shown that when people want to imitate demonstrated arm movements they use internal innate and learned movement models to recreate the details of the whole arm-posture and movement simply by tracking arm end-point trajectories.

Matching the behaviour

Having perceived which of the demonstrator's behaviours to imitate, the imitator has to match the demonstrated behaviour with an equivalent behaviour of its own. The issues already mentioned earlier under "levels of imitation" (section 2.4.1) become particularly important here. What "equivalent" is depends on what the imitator is *trying* to achieve, and what it is *able* to achieve due to its particular body structure. This is known as the correspondence problem (Nehaniv and Dautenhahn, 1998).

There are important representational and algorithmic issues associated with this subtask, revolving around how the demonstrated behaviour is processed and stored and when. More specifically, these issues involve answering the following questions. Is the demonstrated behaviour that registered in the perceptual systems transformed to a representation that the motor systems can use directly or is there some intermediate (possibly symbolic) representation? How could a direct transformation occur and how would the perceptual and motor systems interact in order to perform it? When would this transformation occur: immediately upon registration in the perceptual systems or

when reproduction is required? If there is an intermediate representation, what would its requirements be?

If the demonstrated behaviour is a composite one, addressing these issues might involve decomposing the demonstrated behaviour to its constituents. Is the imitator capable of reproducing all the components and does (s)he know how? If yes, a simple grouping of component actions will suffice in order to reproduce the observed behaviour, but in the opposing case, the reproduction will involve a combination of known (if any) and components that need to be learned.

Analysing the reproduced behaviour

Once the observed behaviour has been matched and reproduced, a post-production analysis should take place for verification and self-improvement purposes. First of all, it should be verified whether the reproduced behaviour did achieve the goals that it was set to achieve. If not, then adaptation mechanisms should be activated in order to account for the failure and attempt to correct it.

2.5 Imitation in robotics

In this section, imitation research that has been performed in the field of robotics will be described, starting from work in robotic assembly tasks, followed by mobile robotics imitation work. In the first instance, the demonstrator is a human while in the second one it is another mobile robot.

2.5.1 Skill acquisition through human demonstration

The potential of imitation to ease the robot programming process was recognised by robotics researchers who realised that instead of going through lengthy and complex programming, robots could learn how to perform various tasks by observing a human demonstrator. Research by (Ikeuchi and Suehiro, 1992; Suehiro and Ikeuchi, 1992; Kuniyoshi et al., 1994; Hovland et al., 1996; Kaiser and Dillmann, 1996; Kang and Ikeuchi, 1997; Yeasin and Chaudhuri, 1997) has successfully used human demonstration to program robots to perform assembly tasks. This work will be presented below,

starting with the systems that utilise visual perception in order to acquire the demonstrator's task knowledge, followed by systems where the knowledge is given to the system directly through the use of a manipulandum, and ending with systems where the motor system's capabilities and limitations are taken into consideration during the acquisition of the knowledge.

Skill acquisition through visual perception

One of the first successful systems for robot learning by imitation and probably the best example of skill acquisition through visual perception is the system developed by Kuniyoshi and colleagues (Kuniyoshi et al., 1992; Kuniyoshi and Inoue, 1993; Kuniyoshi et al., 1994). This system consists of a triple-camera setup which observes a human demonstrator performing an assembly task, in particular constructing various structures using blocks. The system recognises the initial environmental state (the positions of all objects in the workspace) prior to any human demonstration. The human demonstrator performs the task from start to finish, with no interruptions and his hand is located and tracked by the visual system. When the hand approaches a target (block), a "meaningful change detection" routine is initiated. This takes a snapshot of the target before and after the operation, and in conjunction with the environmental model, the system detects the type of operation that has been performed. Finally, the system extracts a high-level symbolic description of the task that the demonstrator performed. The benefit of doing this is that the task description is now applicable also to environmental conditions that differ from the ones present during the demonstration (for example, different positions for the objects). Although limited to pick and place operations, this system was one of the first ones that had the ability to handle recognition of human operations in real-time. Similar systems were also built by (Yeasin and Chaudhuri, 1997; Dillmann et al., 1995).

Systems that were capable of assembly plan construction from observation (APO) were also constructed by (Ikeuchi and Suehiro, 1992; Suehiro and Ikeuchi, 1992), but instead of classifying the human actions from the movements of the demonstrator, the system was focusing on the transitions between different environmental states as perceived by a range or vision sensor, and was attempting to build a 'task model' which was then

matched against a database of known abstract task models in order to generate an assembly program.

Direct skill acquisition

In the approach described above, the actions of the demonstrator were perceived and analysed through a visual subsystem. Other researchers have circumvented this stage by providing the commands that were performed in a form directly usable by the robot (Kaiser and Dillmann, 1996; Kaiser et al., 1995; Friedrich and Dillmann, 1995), in what was termed robot programming by demonstration. There are commonalities with the approaches described above in that the demonstrator does provide example task solutions, but in robot programming by demonstration this is done through the operation of a device that directly controls the robot. A 3D joystick was used (Kaiser et al., 1995) by the demonstrator to perform the task, and the performed actions were recorded and played back when the robot was required to perform the task on its own.

Several other devices have also been used in order to transfer the task data from the human demonstrator to the robot, including position sensors that are attached to the body of the demonstrator (Hovland et al., 1996), and cybergloves (Lee and Xu, 1996). The different approaches are not, of course, mutually exclusive and there has been work that utilises more than one input device to enhance the quality of the task recognition (Kang and Ikeuchi, 1997).

Involving the motor system

In the previous examples, the motor system and any constraints it might have are not taken into account during the perception process. The flow of information is unidirectional, from perception to motor commands. Kawato's bidirectional theory (Kawato, 1992) allows information to flow *from* as well as *to* the motor system: the dynamical properties of the motor system are taken into account during movement planning and generation. Movement trajectories are represented as sets of "via-points" that the imitator has to go through in order to smoothly follow this trajectory; demonstrated movements are recognised if the number and locations of the via-points extracted during the demonstration match with one of the observer's existing sets. This approach has

been demonstrated in the learning of the Japanese game "Kendama" by a humanoid-type arm (Miyamoto et al., 1996) as well as recognising words from cursive handwriting (Wada and Kawato, 1995), and it was one of the first approaches that had the very interesting property that the motor system is utilized in order to do the perception too. The importance of involving the motor system in the perception of an action is also advocated by (Schaal, 1999).

2.5.2 Skill acquisition through robot demonstration

The advantages of imitation were also utilised in a different domain, that of mobile robots (Dautenhahn, 1994; Demiris, 1994; Hayes and Demiris, 1994; Dautenhahn, 1995; Demiris and Hayes, 1996; Billard and Hayes, 1998; Billard and Dautenhahn, 1998; Billard, 1999). The tasks revolve around the acquisition of navigation skills, identifying good and bad teachers and grounding language. These will be described below.

One of the first examples of using imitation in mobile robots was in the context of learning how to negotiate the different types of corners in a maze by imitating another mobile robot, knowledgeable in the task (Demiris, 1994; Hayes and Demiris, 1994). Two robots were placed in a maze environment: the teacher one knows how to handle each corner[2] while the learner does not. The learner is equipped with a camera and utilises it in order to maintain a distance between itself and the imitator, effectively imitating the movements of the demonstrator in the two dimensional plane. While it is doing that, it associates the actions that it is performing due to the imitation, with the environmental configurations that it is perceiving, thus learning which is the right action to perform at each environmental state.

This approach of learning through movement imitation has been taken further by the work of (Dautenhahn, 1994, 1995). The learner robot follows the teacher robot by trying to establish and maintain contact with it in a hilly landscape environment ("Huegellandschaft"). This environment adds an interesting new dimension to the two dimensional scenario used above: the hilly parts and the inclination that the robots have to assume while traversing them gives the ability to add an energy consumption

[2] There are three different situations, left-turn corners, right-turn corners - both at ninety degrees, and no corners at all.

or "movement difficulty" parameter to the scenario. A robot learner following a robot teacher in this environment learns whether this teacher is good or bad, based on whether following it results in high or low consumption. What Dautenhahn (1995) has shown is that imitation can be used to probe the identity of other robots in a social environment[3], in a similar way that Meltzoff has been postulating for human infants.

Imitation has also been used to ground a simple language (Billard and Hayes, 1998; Billard and Dautenhahn, 1998; Billard, 1999): the learner follows the teacher and learns to associate a vocabulary transmitted by the teacher (through a radio modem) with its perceptions. This work demonstrated that a simple movement imitation strategy can also be a useful technique for learning a language, since it gets the two robots to share the same environmental context.

2.6 Summary

In this chapter, theoretical and empirical imitation work on robots and animals was presented. Work in assembly robots has followed a traditional "perceive-recognise-reproduce" cycle, while mobile robotics work has attempted to circumvent the recognition part of the cycle and try to learn additional skills utilising the imitation mechanism as a starting point.

Apart from (Dautenhahn, 1994, 1995), the majority of the robot work has concentrated on the matching mechanism and identifying a beneficial behaviour to imitate subtasks, and has ignored the issues of picking the right demonstrator to imitate. This thesis will also focus on the matching mechanism, and assume that the demonstrator has already been selected. In contrast with the robot assembly work mentioned earlier, it will attempt to adhere to the data available on the mechanisms underlying movement matching and imitation in biological systems.

There has been work investigating imitation in human infants and adults from psychological, pathological and brain scanning perspectives, and in monkeys from a neurophysiological perspective. Description of this work is embedded in the chapters that

[3] Is the robot I am following a conspecific (does it behave in a similar way to me), is it a good or bad teacher for me (are its actions beneficial for me)?

follow, closer to the theoretical and computational work that it has provided the inspiration for.

Chapter 3

Passive Imitation

In this chapter, a computational architecture inspired by Meltzoff's AIM hypothesis (Meltzoff and Moore, 1983, 1989) will be presented followed by a description of its implementation on a stereo-vision robotic head, in the context of robotic imitation of a human demonstrator's head movements. The chapter concludes with an examination of the biological plausibility of the computational architecture that was implemented.

3.1 Background

In the previous chapter, a range of robotic attempts to imitation were described, most of which fell into the category of what is termed "passive imitation", where the imitation process proceeds serially through three stages: perception, recognition, reproduction.

Approaches by (Hayes and Demiris, 1994; Dautenhahn, 1994, 1995; Demiris and Hayes, 1996; Billard, 1999) have attempted to follow a different approach by trying to devise imitation mechanisms that will work directly *without* a recognition stage. This line of work is relatively new, but it makes an important distinction: the imitator is not imitating because it is understanding what the demonstrator is showing, but rather, it is understanding it *because* it is imitating. Imitation is used as a mechanism for bootstrapping further learning and understanding.

The distinction between the two approaches is new in the field of robotics but not in psychology. Researchers studying imitation in infants have made a similar distinction while formulating hypotheses regarding the mechanisms underlying early infant im-

itation. Meltzoff and Moore (1977) first reported young infants, between 12 and 21 days old in the original report, being able to imitate both facial and manual gestures, including tongue protrusion, mouth opening and lip protrusion. The experimenters suggested that the infants are able to represent visual and proprioceptive information in a form common to both modalities. These results were against the popular belief at the time, that infants are only capable of imitation after 8-12 months from birth, and that imitation abilities are a result of the infant's cognitive development. However, the phenomenon proved to be a robust one, and was replicated in many other laboratories[1], and shown to be present even in newborn infants (Meltzoff and Moore, 1989, 1983; Reissland, 1988). There is also a report of the same phenomenon with a infant chimpanzee (Myowa, 1996).

Various hypotheses regarding the mechanisms underlying this phenomenon were compared by Meltzoff and Moore (1989), including the "innate release mechanism (IRM) model" which postulates that the demonstrator's behaviour simply triggers and releases equivalent fixed-action-patterns (FAPs) by the infant. The IRM model relies on the existence of a set of FAPs, but there isn't a precise specification of what this set is (Meltzoff and Moore, 1989). IRM was judged to be an unlikely candidate for two reasons:

- The range of actions imitated was wide, which would mean that the infant would have to have a large number of FAPs in its repertoire.
- The fact that the infants attempt to and succeed in improving the quality of the imitated act (Meltzoff, 1981).

(Meltzoff and Moore, 1983, 1989) put forward the "Active Intermodal Mapping" hypothesis which postulates that the infants use the demonstrator's states, perceived visually, as a target against which to direct their own body states, perceived proprioceptively. This hypothesis is particularly attractive in the case of facial or head movements for which the infant has no other way of knowing the state of its own body other than proprioception. The existence of a mechanism that matches stimuli between different modalities has also been advocated by Maurer (1993), but while Meltzoff's AIM

[1] For a complete list see (Meltzoff and Moore, 1994)

mechanism appears to be activated as a choice made by the infant, Maurer argues that the infant's intermodal matching of stimuli is a by-product of what was termed "neonatal synesthesia": the infant *confuses* input from the different senses. The infant, it is argued, does not register the modality that the stimuli appeared in but rather it responds to changes in the stimulation's intensity summed over all of the undifferentiated sensory modalities. Synesthesia is hypothesised to be a normal stage of early infant development: it is argued that the primary sensory cortex is not very specialised in infants, but with development it becomes so, the senses become more differentiated, and "true" intermodal matching develops. Whatever the exact mechanism is, the ability of the infant to match stimuli between modalities is well documented, and has been demonstrated between other modalities in addition to the visual/proprioceptive cases mentioned earlier, for example tactual/visual intermodal matching (Meltzoff, 1981, 1993).

At this stage it is useful to draw parallels between this work and the assembly and mobile robot imitation work described earlier. There are a lot of commonalities between the passive imitation model in robots and the IRM model in infants. Both rely on the existence of a set of predefined action patterns, which are triggered after the perception and classification of the visual input. This set, at least in the robot work (as described in the previous chapter), is fixed, and frequently tuned to the requirements of the task in hand.

The mobile robot imitation work (Hayes and Demiris, 1994; Dautenhahn, 1995) is closer to the AIM hypothesis model, since the robots do not attempt to recognise the type of action performed by the demonstrator, but imitate directly. However there is a difference between AIM and the approach followed by the mobile robot researchers: the robot imitators do not attempt to match the demonstrator's state with their own (as AIM suggests), but rather try to maintain a quantity constant, which in the case of robot following is the distance between the two robots, i.e. there is a "virtual tethering" between them.

The next section presents a computational architecture that follows the AIM model more closely, followed by the implementation of this architecture on a head-movement imitation scenario.

3.2 The Architecture

The basic components of the architecture designed are shown in figure 3.1.

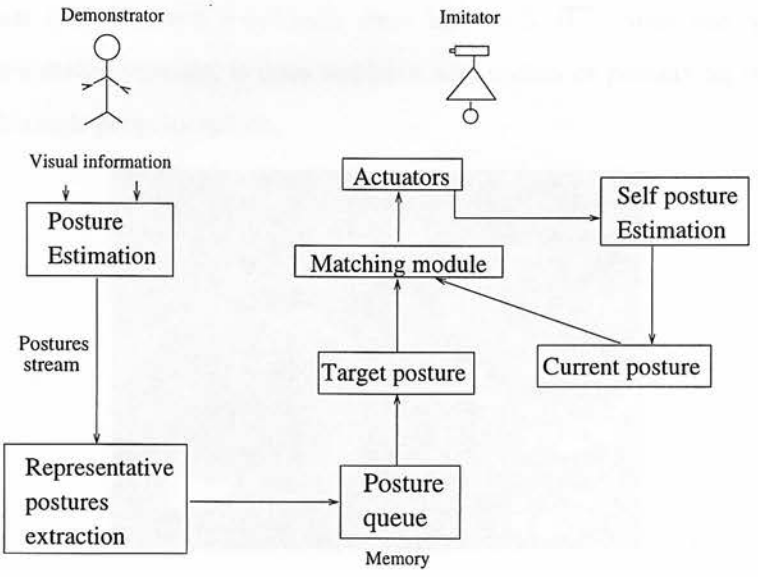

Figure 3.1: The computational architecture for passive movement imitation

The visual stimuli from the visual perception modules are fed into the posture estimation module, which at each iteration outputs the current postural state of the demonstrator[2]. This posture stream is stored in memory after being filtered so only the "representative postures" are retained. The postures are then fed into the movement matching module which outputs the motor commands needed to match these postures with equivalent postures by the imitator, perceived proprioceptively. Each of these modules will be described in turn in the following subsections, right after the presentation of the scenario that was selected and the robotic platform that was used.

3.3 Experiments

3.3.1 Experimental scenario - human head movement imitation

The scenario chosen to test the architecture was human head movement imitation. A human demonstrator positions his head within the robotic head's field of view,

[2] Posture is defined here as the set of angles between all connected body parts of the agent.

and performs a series of head movements while the robot remains still. When the demonstrator completes the head movement(s) it signals the robot (via a keyboard) to start the imitation. This scenario was chosen since it places the imitator in the same situation that Meltzoff's subjects were in: while the robot has access to the demonstrator's states visually, it does not have any means of perceiving its own states other than through proprioception.

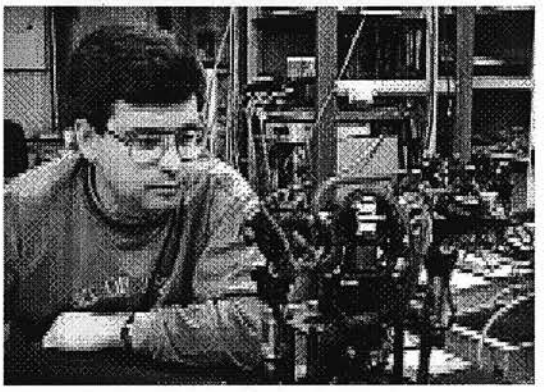

Figure 3.2: The human robot scenario

3.3.2 Experimental platform - ESCHeR

ESCHeR (E[tl] S[tereo] C[ompact] He[ad for] R[obot vision], figure 3.3) was designed and built in Japan, at the Electrotechnical Laboratory (Kuniyoshi et al., 1995a), and was largely inspired by the properties of biological visual systems. This binocular head is equipped with foveated wide-angle lenses (Kuniyoshi et al., 1995b) which exhibit a wide field of view ($\approx 120^o$) for global observation and a high resolution fovea ($\approx 20pix/deg$) for precise attention, and can perform motions with peak velocity and acceleration comparable to human capabilities ($400deg/sec$) for vergence velocity).

ESCHeR is capable of real time image processing and for the purposes of these experiments, it was computing the optical flow at frame rate (30 Hz) in 1600 locations (40x40) for both left and right images. Routines developed for tracking experiments (Rougeaux and Kuniyoshi, 1997) were re-used here to calculate the optical flow.

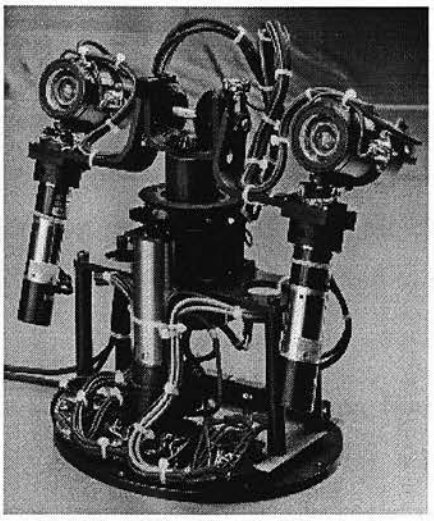

Figure 3.3: ESCHeR: ETL's high performance stereo-head (Kuniyoshi et al., 1995a).

3.3.3 Architecture implementation

This section describes how the computational architecture was implemented for this scenario. First, the perception and representation subsystems will be described, followed by the description of the matching subsystem.

Perception and representation modules

The demonstrator's head pan and tilt rotations are estimated using optical flow information and Kalman filtering (Brown, 1995). To simplify the problem, it is assumed that the optical flow observed during head motions is mainly produced by the rotational components. The head translations are neglected, since it is impossible for the robot to imitate them, and the demonstrator is asked to minimise any such translations.

The flow fields induced by the head rotations are retrieved using a standard gradient-based optical flow algorithm combined with an IIR recursive filter described in Fleet and Langley (1996). The vertical and horizontal components *(u,v)* are computed using a flow segmentation algorithm described in Rougeaux and Kuniyoshi (1997). Then the pan and tilt rotations of the observed head are estimated using the following state equations in two independent Kalman filters:

$$\theta_{pan_{k+1}} = \theta_{pan_k} - U dt u_k + \frac{dt^2}{2} g_k \tag{3.1}$$

$$\theta_{tiltk+1} = \theta_{tiltk} - Vdtv_k + \frac{dt^2}{2}h_k \quad (3.2)$$

where g_k and h_k are Gaussian white-noise processes modelling the acceleration, and U,V are constants that take into account the resolution of the lenses (Kuniyoshi et al., 1995b). Since high-precision posture estimation is not required in this experiment, no calibration is needed, and U and V can be roughly tuned to limit the amplitude of the head rotations.

A refinement process was added after the realisation that storing all the postures (estimates of which are acquired at frame rate - 30 Hz), a large amount of which are consecutive ones, is not necessary. This process selects the postures that are sufficient to define the sequence to be reproduced, the "representative" ones. The extraction of the representative postures utilises a simple algorithm which keeps the posture in memory if the posture is a local min/max value in any of its constituent axes[3]. Note that, although in general there exist possible axes of analysis both at the perceptual (allocentric) and the motor (egocentric) frames of reference, the correspondence is simplified since the two agents are facing each other, which means that the perceptual and motor frames (centered at the heads of the two agents) are simply mirror images of each other.

Matching Module

In order to achieve the target postures that were stored by the perceptual and memory modules, the target posture is compared with the current posture, as measured by the robot's self-posture estimation module, and depending on the relation between the pan and tilt components of the target and the current posture, one or more motor commands of the form "move upwards", "move leftwards" etc. are initiated, and remain active until the module determines (based on proprioceptive signals) that the target posture has been reached. The self-posture estimation is done by having the robot head initialise to (0,0) at the beginning of the experiment and using the values of the encoders to get current estimates of the self posture.

[3] Specifically, if there exists an axis (either x or y in this case) so that the value of the posture at *frame* has the same relationship (one of "smaller than" or "greater than") with the value of the posture at *frame+1* as it has with the posture value at *frame-1*

There are two main reasons for having the matching process work like this:

- **Perturbation tolerance:** even if the movement is perturbed during execution, the body part can still reach the intended target since the commands issued are dependent on the difference between the current and the final posture, and are not output on an open-loop, feed-forward manner.
- **Biological plausibility:** there is some evidence that at least some types of limb movements are controlled by constantly comparing an estimate of the current postural state of the limb with a target value (Desmurget and Prablanc, 1997). The issue of biological plausibility will be revisited at the discussion section at the end of the chapter.

3.3.4 How does the system perform?

Experiments were performed with humans sitting in front of ESCHeR and performing various head movements (figure 3.2). An example movement sequence is shown in figure 3.4: the demonstrator, starting from a face-to-face position with the robot head, rotates his head left-right twice, before returning to his initial position, in a sequence roughly resembling a 'no-no' gesture. Snapshots 2, 4, 6, 8 and 9 roughly correspond to the 'representative' postures extracted during the demonstration process. Figure 3.5 shows snapshots of the robot going through these postures.

The system is able to cope with the imitation of a variety of human head movements irrespective of the duration of the movement and its speed. It was observed that, by activating the representative posture extraction module, apart from cutting down on memory requirements, the robot was performing a more smooth movement during the imitation phase. This was due to the fact that the robot was now issuing start/stop commands less frequently since there were fewer intermediate postures to go through. This has to be traded against the desired quality of the trajectory of the movement since the representative module tends to take the shortest route between two points, therefore not following circular segments along the trajectory precisely. For example, if the demonstrator performs a circular movement with his head (a "head roll"), the resulting movement will be more of a diamond shape rather than circular, since the

Figure 3.4: The demonstrated head sequence

four postures that will be extracted will be the four points of change of direction[4]. Any compromise in quality can also be avoided (if required) by deactivating the representative posture extraction module, or by implementing a mechanism that, in addition to the representative postures above, includes sample postures at regular intervals. The activation of such mechanism can also be made dependent on the levels of attention of the observer so that parts of the demonstration significant or interesting to the observer can be sampled at smaller intervals.

Since the robot is capable of movement only in the pan and tilt direction, rotational movements along the third axis could not be imitated. Since the system assumes that the optical flow that is observed is due to mainly rotational movements, it interprets optical flow due to translational movements as the rotational movements that would have generated the equivalent optical flow.

[4] This is usually avoided in many robotic implementations since these 'via points' are not reached, but rounded off, allowing, for example, a polygon sequence to imitate a circle very well.

Figure 3.5: The resulting robot head movement. The arrows indicate where the robot head point towards at each snapshot. A video clip with this demonstration can be found at *http://www.dai.ed.ac.uk/daidb/people/homes/johnde/*

Videos with example movements and their imitation by the robot head can be found in *http://www.dai.ed.ac.uk/daidb/people/homes/johnde/*. The results of implementing this architecture in this scenario have been replicated (Schofield, 1998) with a different robot platform, consisting of a robotic head with a single camera.

3.4 Discussion

The architecture above has the following advantages: it is general enough to be able to imitate any kind of demonstrated movement that the hardware of the imitator system

can afford. It does so by having a very low requirement on needed information: the postures of the demonstrator, perceived visually, and those of the imitator, perceived proprioceptively. The choice of posture as the unit of representation is not arbitrary. The postures of the demonstrator and imitator are always well defined and computable. In addition, postures have a high biological significance: animals frequently use them for communicative purposes (Bruce and Green, 1990; Groothuis, 1993), e.g. threat, appeasement and mating postures, and human body language. Their biological significance might even have led to the development of specialised feature detectors that respond selectively to postures. Indeed, work by Perrett and his colleagues has shown the existence of cells in the superior temporal sulcus (STS) area of the monkey's brain, that respond when a demonstrator assumes certain postures, for example, cells that are responsive to specific head views (Perrett et al., 1990, 1991). Cells selective to other body parts have also been reported (Tanaka, 1993), see also (Carey et al., 1997) for an overview.

Similarly, as Tillery et al. (1996) point out, physiological studies throughout the somatosensory system have revealed discharges related to own static limb postures: unit activity is usually monotonically related to changes in joint angle. The degree of accuracy of a proprioception-based estimate of the static posture is not completely determined, and it has been shown that it improves when visual information about the state of the body part is also available (Desmurget et al., 1995), or is even being partially substituted by it when proprioception is not available in deafferented patients (Ghez and Sainburg, 1995). Scott and Kalaska (1995) demonstrated that cell activity in the monkey motor cortex is highly sensitive to changes in arm posture even if the resulting hand trajectory remains similar.

Finally, evidence that, at least some type of movements are controlled on the basis of a joint angular error has been provided by Desmurget and Prablanc (1997) who have shown that three-dimensional upper-limb movements are controlled via a mechanism that is comparing an estimate of the current postural state with a target value.

3.5 Summary / What next

In this chapter, a computational architecture that closely follows Meltzoff's AIM hypothesis was described, and its implementation was presented for a scenario featuring imitation of human head movements. The architecture has low signal requirements, and it relies on the existence of always computable information, i.e. the postures of the demonstrator and the imitator. By relying on information known to exist in the human brain and requiring only an intermodal matching mechanism that is known to be within the capabilities of infants, the architecture manifests itself as an attractive model for the infant imitation abilities. Could it be a universal model for movement imitation for later ages too? There are two issues that are against this. First, by virtue of its design, there is no concept of known and novel movements: all demonstrations are processed and imitated through the same mechanism. In addition, there is a clear separation between perception and action: the motor system is involved only at the late stages of imitation. Both these aspects have been challenged by recent biological data, and in particular human brain activation data, that indicate that actions are processed differently if they are known to the imitator than if they are novel, and that the motor system is already actively involved during the perception phase of the imitation process (these data will be described, among others, in chapter 6). The next chapter introduces an architecture that tackles these issues, and explains these biological data better. However, it would be premature to dismiss this "passive" architecture as invalid. In chapter 5, this architecture will be combined with the "active" architecture of the next chapter: it will be used as a learning component in what will be a dual-route active-passive imitation architecture.

Chapter 4

Active Imitation

4.1 Introduction

In this chapter, an architecture that tightly couples the perception and the generation of an action will be described. The concept of internal forward models will be introduced, and the imitation architecture will subsequently be developed as a parallel set of behaviours paired with forward models. Using a dynamics simulator of a thirteen degrees of freedom robot it will be demonstrated how such an architecture can be used to generate an action as well as perceiving it when generated by others.

4.2 Background

The architecture that will be described in the next section makes extensive use of the concepts of behaviours and of forward models.

A forward model of a controlled object (a 'plant' as it is known in the control literature) is a function that, given the current state of the plant and a control command to be applied on it, outputs the predicted next state (figure 4.1). Forward models are frequently used in control engineering, since they provide at least two major advantages:

- Provision of rapid internal feedback: using a forward model the outcome of motor commands can be predicted and used immediately in an internal feedback loop, making feedback control possible even in situations where, due to large delays in the provision of real feedback (the typical situation in sensorimotor cases),

feedback control would be infeasible.

- Controller improvement through mental practice: the results of the controller commands can be predicted and acted upon without actually executing the commands.

For the purposes of this thesis, a behaviour is defined[1] as a function that, given the current state of the plant and the target goal(s), outputs the control commands that are needed in order to achieve or maintain the goal(s). Target goals might be implicit or need to be made explicit. For example, for a pick-object behaviour, the target object to be picked up must be stated explicitly and fed to the behaviour, while for a head-nodding-yes behaviour, the target goal (i.e. moving the head downwards) is already defined implicitly and the current state is enough to determine the motor commands needed to execute this behaviour. A behaviour is similar to what is known in the control literature as an 'inverse model', however, contrary to behaviours, inverse models do not usually utilise feedback about the current state, but output commands in a feed-forward manner. The boundary between behaviour and inverse model however, is not a rigid one since, as (Wolpert and Kawato, 1998) pointed out, "even control strategies, such as feedback control, which do not explicitly invoke an inverse model can be thought of as implicitly constructing an inverse model".

Combinations of forward and inverse models have been used for various applications such as arm trajectory formation (Wada and Kawato, 1993) and supervised learning (Jordan and Rumelhart, 1992) among others. Internal forward and inverse models have also been hypothesised to exist in the human brain (Wolpert et al., 1998), where they are utilised for a variety of tasks including sensorimotor integration (Wolpert et al., 1995), and motor control (Miall and Wolpert, 1996; Wolpert and Kawato, 1998).

4.3 The architecture

In this section, the active imitation architecture will be described, starting initially from how this architecture can be used to generate behaviours, followed by how such

[1] Note that there are several other definitions of the word 'behaviour' in other research areas, for example behaviour-based robotics (Arkin, 1998), and ethology (Hinde, 1982)

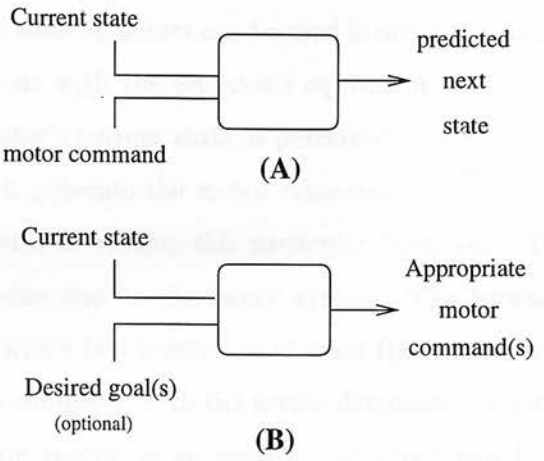

Figure 4.1: Input-output diagrams for forward models (a) and behaviours (b)

an architecture is used in order to understand demonstrated behaviour.

The fundamental structure of the architecture is a behaviour paired with a forward model (figure 4.2). In order to execute a behaviour within this structure, the behaviour module receives information about the current state (and, optionally, of the target goal(s)), and it outputs the motor commands that it believes are necessary to achieve or maintain the implicit or explicit target goal(s). The forward model provides an estimate of the next state which is fed back to the behaviour, allowing it to adjust any parameters of the behaviour[2].

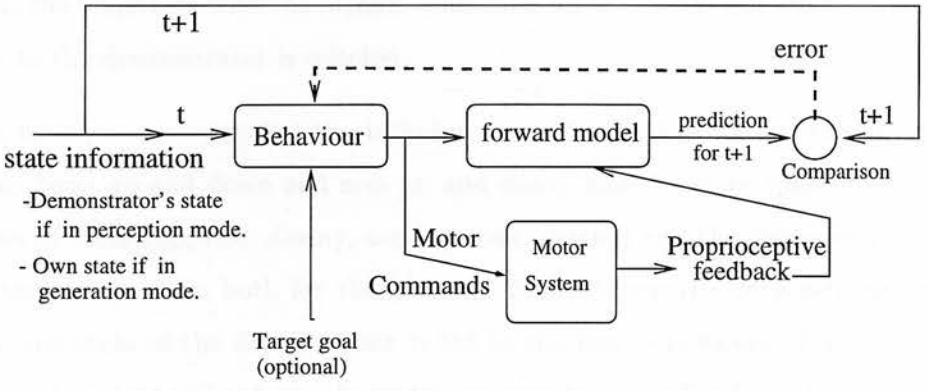

Figure 4.2: The basic building block: a pairing between a behaviour and a forward model

[2] An example of this, as will be shown in the next section (implementation), is adapting the gains of the PID controller used to implement a behaviour in order to achieve different movement speeds.

More importantly, the same structure can be used in order to match a visually perceived demonstrated behaviour with the imitator's equivalent motor one. This is done by feeding the demonstrator's current state as perceived by the imitator to the behaviour modules and having it generate the motor commands that it would output *if it was in that state and wanted to execute this particular behaviour.* The motor commands are inhibited from being sent to the motor system. The forward model outputs an estimated next state which is a prediction of what the demonstrator's next state will be. This prediction is compared with the actual demonstrator's state at the next time step. This comparison results in an error signal which can be used to increase or decrease the behaviour's confidence value, which is an indicator of how confident the particular imitator's behaviour is that it can match the demonstrated behaviour.

Figure 4.3 shows the complete architecture which consists of several of the structures that were described above, operating in parallel. When the demonstrator executes a behaviour, the perceived states are fed into the imitator's available behaviours which generate motor commands that are sent to the forward models (relevant only to body parts related to the particular behaviour). The forward models generate predictions about the demonstrator's next state which are compared with the actual demonstrator's state at the next time step, and the error signal resulting from this comparison affects the confidence values of the behaviours. At the end of the demonstration (or earlier if required) the behaviour with the highest confidence value, i.e. the one that is the closest match to the demonstrator is selected.

As an example, lets say that the imitator currently has four behaviours in its repertoire: head up and down and arm up and down, and the state space of the agent consists of (head{up, rest, down}, arm{up, rest, down}) and the demonstrator starts from the rest position both for the arm and head. When the demonstration is initiated, the state of the demonstrator is fed to the four behaviours. Each behaviour assumes that state and outputs the motor commands that will achieve their respective target goal (e.g. the head up behaviour will apply the appropriate forces to the neck joints to raise the head). Each of the forward models receives the commands from its associated behaviour and calculates what the next state would be if these commands were executed (a description on how is this achieved can be found at section 4.4.3).

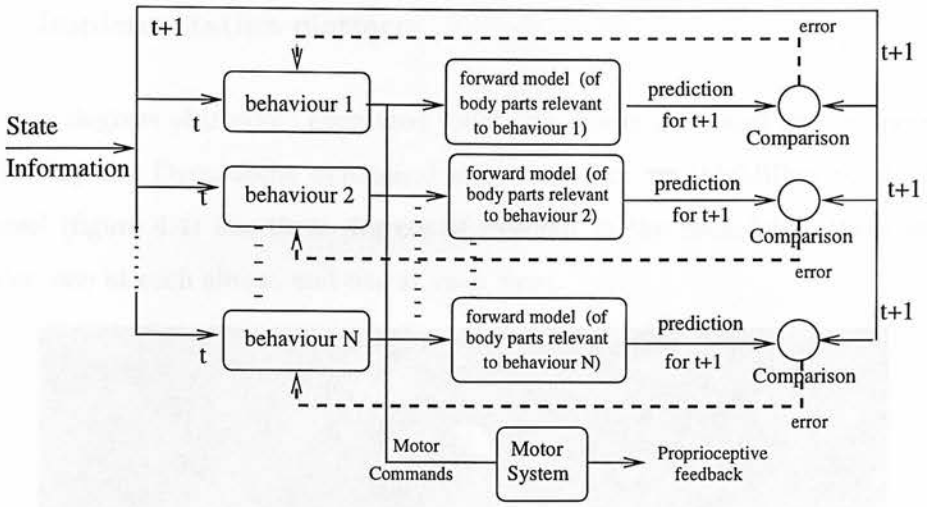

Figure 4.3: The architecture consists of behaviours paired with forward models

In this example, the four forward models would output (head up), (head down), (arm up), and (arm down) respectively, which are the predictions on what the next state of those body parts of the demostrator will be. These outputs are compared with the actual state that the demonstrator assumes next, and the ones that are correct result into reinforcement for the corresponding behaviour. The following section describes experiments demonstrating this architecture using a 13 DOF dynamically simulated robot.

4.4 Experiments

This section presents and analyses the results of implementing the architecture above on a dynamics simulator of a thirteen degrees of freedom robot using as a test set the movements of the International Standard Semaphore Code (ISSC). The results show that the architecture is capable of correctly selecting the appropriate behaviour even when the demonstrator and the imitator have significantly different dynamics. This is demonstrated both in the context of single movements ('letters') and in sequences of movements ('words').

4.4.1 Implementation platform

A thirteen degrees of freedom simulated robot was constructed and its dynamics simulated using the DynaMechs dynamical simulation library (McMillan et al., 1995). 'Bouncer' (figure 4.4) has three degrees of freedom at the neck joint, three at each shoulder, one at each elbow, and one at each wrist.

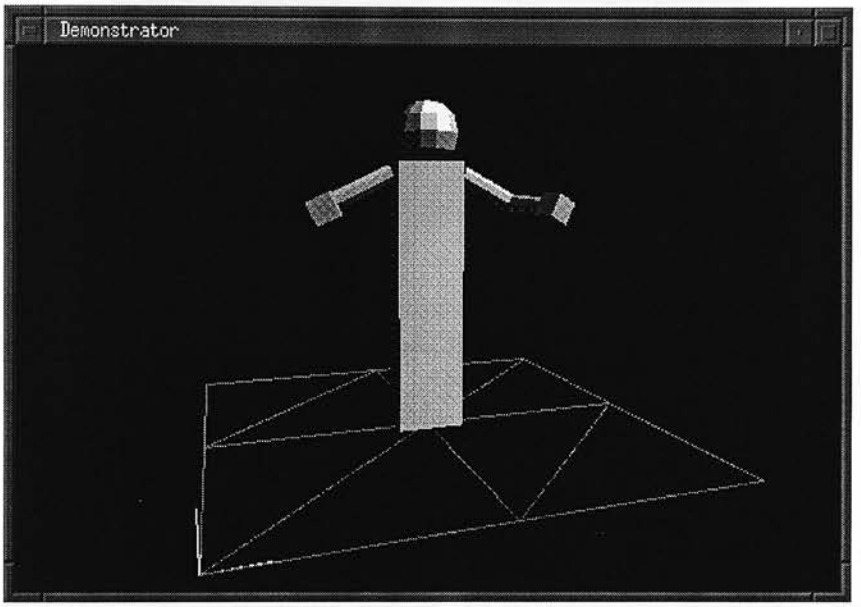

Figure 4.4: 'Bouncer', the thirteen DoF dynamically simulated robot

Bouncer operates under the effect of gravity, so if no forces are applied to a joint, the connected body part moves toward the ground. Movement is also subject to friction at the joints. The full experimental platform (figure 4.5) consists of two simulated robots, a demonstrator and an imitator, with similar body structure. In some of the experiments that follow, the dynamics of the two robots were the same, while in other they were different. The imitator is allowed to read the demonstrator's postural states (joint angles) in a crude simulation of visual capabilities. To account for the fact that in the case of the imitator, real vision and proprioception never result in perfectly correct values of the visually perceived demonstrator states and proprioceptively perceived imitator states, uniformly-distributed random noise in the range of [-10%, +10%] is added to both of them before they become available to the imitator.

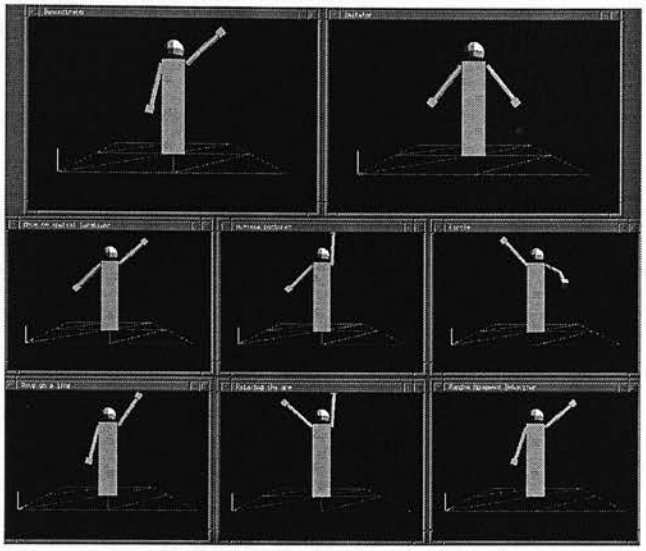

Figure 4.5: The full platform - demonstrator is top left, imitator top-right, and the six windows below display the behaviours that the imitator is currently generating internally; the windows currently display letters E, N, L, K, I, E, T and E respectively

4.4.2 Implementation domain

The ISSC is an alphabet signalling system based on having the arms extended in various positions/postures representing each of the letters of the alphabet. The test set which will be used here is the set of movements that, starting from a rest position for the arms, achieve the various postures of the ISSC. Appendix A shows the correspondence between the final states of the movements and letters[3]. For example, in figure 4.5 the eight windows are a snapshot of behaviours which currently show movement towards letters E, N, L, K, I, E, T, and E respectively. There is no standardised set of movements used in research of movement imitation (although interesting suggestions, such as the Macarena dance (Mataric et al., 1998a,b; Demiris and Mataric, 1998) have been put forward). The reason for selecting this as a test set is twofold:

- It is a well defined set of movements.
- It has the capacity to support movement combinations of arbitrary length in a meaningful, principled way, since there is a correspondence between the final states of each movement and alphabet letters, thus the capacity to form syllables,

[3] The formal ISSC involves holding a flag in each hand but this is not used here.

words and so on.

4.4.3 Implementation of the architecture

This section describes how the architecture was implemented for these experiments. This involves the description of the implementation of three architecture components: the behaviours, the forward models, and the confidence building formula.

Implementation of the behaviours

Behaviours were implemented using a proportional-integral-derivative (PID) controller, that drives the controlled body part(s) through the key postures constituting the behaviour. The PID controllers, one for each of the thirteen controlled joints, output torque values which are calculated by summing three terms:

$$T(t) = T_p(t) + T_i(t) + T_d(t) \tag{4.1}$$

where $T_p(t)$, $T_i(t)$, and $T_d(t)$ are the proportional, integral, and derivative terms respectively, all of which are dependent on the error between the current state and the target state. More specifically, if we take $e(t)$, the error at time t, to be the difference between the target state and the plant's state at time t, then the formulas for the three parts are as follow:

- The proportional part is a simple feedback-based term:

$$T_p(t) = K_p e(t) \tag{4.2}$$

- The integral part is given by

$$T_i(t) = K_i \int^t e(t)dt \tag{4.3}$$

and is introduced to allow a system that has an error in the steady-state to take corrective action, even if the error is very small, provided that the error had the same sign over a long period of time

- The derivative part is given by

$$T_d(t) = K_d \frac{de(t)}{dt} \tag{4.4}$$

and is used in order to anticipate the future behaviour of the error signal by using corrective action based on the rate of change in the error signal. This has the effect of reducing the undesirable overshoot and time it takes for the controlled object to settle at the target values (in this case, angles).

An important issue to note is that the PID controllers perform best within a specific range of gain values; if they are not tuned within this range, they perform sub-optimally or might even lead to a destabilization of the controlled plant. In the experiments reported below, the optimal gains were determined experimentally, although techniques for the automatic tuning of the controllers also exist (Hagglund and Astrom, 1996).

The gain parameters K_p, K_i and K_d of equations 4.2, 4.3, and 4.4 all start having their optimal settings, but are allowed to adapt in order to reduce the prediction error between the anticipated states produced from internally executed behaviours and perceived demonstrator states. A simple adaptation mechanism was implemented for this: at each iteration, if the prediction for a joint angle value proves to be different from the actual value, the corresponding gain K_p for the PID controller that controls that joint angle is increased or reduced (depending on whether the prediction underestimated or overestimated the actual value) by a small constant amount[4]. However, although the gain parameters are allowed to fluctuate, (experimentally determined) upper and lower bounds are imposed in order to prevent the controller from outputting very high torque values and destabilising the plant. As it will be demonstrated later, this renders the perception of particular instances of some behaviours impossible.

Implementation of the forward models

The DynaMechs simulation package (McMillan et al., 1995) includes libraries for simulating rigid body dynamics, and these were used in order to implement the forward models. The procedure used is based on Featherstone's original Articulated Body (AB)

[4] This usually amounts to 0.25% of the initial optimal settings

dynamics algorithm for simulating the dynamics of chains of rigid bodies (Featherstone, 1983) but includes modifications that improve the efficiency of the computation of AB inertias (McMillan and Orin, 1995). The procedure involves four steps:

- Applying the forces supplied by the behaviour, taking into account the current state (joint positions and velocities) of the robot;
- Calculating the forces exerted (including joint friction and gravity) and the AB inertias that are present in each joint;
- Calculating the resulting accelerations recursively for each body part starting from the torso and moving towards the wrist;
- Calculating the new state (joint positions and velocities);

Details of the equations used by DynaMechs to calculate the above are given in (McMillan and Orin, 1995; McMillan, 1994).

Although in the experiments reported here, the forward models are directly coded in, they can also be learned by randomly generating motor commands, and using the resulting actual state as the target output state for the forward model, in what is sometimes called "motor babbling" (Bullock et al., 1993; Jordan and Rumelhart, 1992) which is considered an important stage in the development of infants (Meltzoff and Moore, 1997; van der Meer et al., 1995)

Confidence building

The forward models output predictions for each of the joints, which are compared to the actual values that come at the next time step. The prediction error is given by:

$$E(t) = \sum_{i=1}^{N} |x_i(t) - px_i(t)| \tag{4.5}$$

where $x_i(t)$ is the actual value of the demonstrator's joint angle (with the noise added) at time t, and $px_i(t)$ is the predicted value that was given by the forward model for

time t. N is the number of joints involved in this behaviour. The confidence value of the behaviour is then accumulated according to the following update rule:

$$C(t) = \begin{cases} C(t-1) + k\frac{1}{E(t)} & \text{if } E(t) < A \\ C(t-1) - kE(t) & \text{otherwise} \end{cases} \tag{4.6}$$

where $C(t)$ is the confidence of a behaviour at time t, A is a constant threshold value, which is set experimentally, and k is a gains constant, which is also set experimentally.

The reasoning behind adopting this formula is that reinforcement should be related to how well or not a behaviour is predicting the perceived demonstrator states. Equation 4.6 gives a higher reward value to predictions closer to the perceived state than to ones that, although acceptable, are further away. Similarly with negative reinforcement - larger errors in the prediction carry higher penalties than smaller ones.

4.4.4 Experimental results

Two sets of experiments were performed; one set where the behaviours demonstrated were single movements (one letter), and one set where the demonstrated behaviours were sequences of movements (words). Each set of experiments was performed under three experimental conditions:

L-L/H-H : Imitator and demonstrator have similar dynamics by having similar weight characteristics, either lightweight (L) or heavyweight (H). L and H are 100% different, i.e. H has double the weight of L.

L-H : The demonstrator is lightweight and the imitator is heavyweight.

H-L : The reverse of L-H.

This grouping of different dynamics into lightweight and heavyweight bands was made since small variations in weight do not have any noticeable effect.

A final set of experiments demonstrates the limitations of this architecture; behaviours demonstrated at speeds unattainable by the imitator are not perceived although within the repertoire of the imitator.

Single actions

This set of experiments consisted of the demonstrator performing a behaviour that was composed of a single action and the imitator observing it having a set of behaviours in its repertoire. The number of behaviours is not important since the behaviours run in parallel and they are independent of each other[5]. Experiments with six behaviours are shown for graph clarity reasons. It is important to note though that in the experiments reported in this chapter, the demonstrator's behaviour was in the imitator's repertoire.

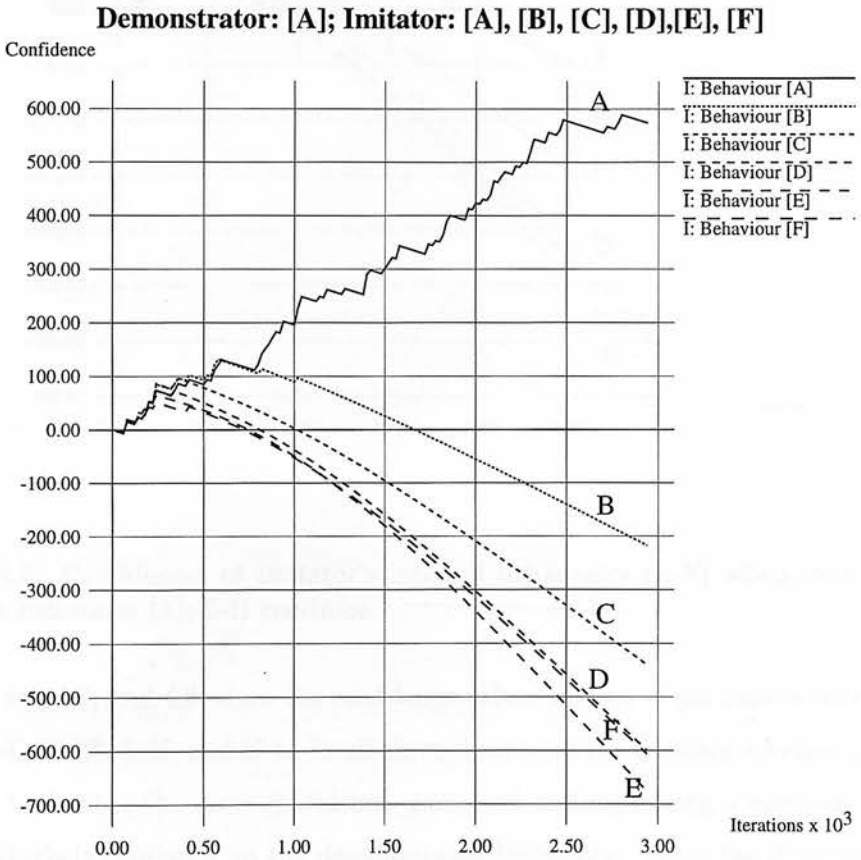

Figure 4.6: Confidences of imitator's internal behaviours [A-F] when demonstrator executes behaviour [A]; L-L condition

[5] Only their confidences need to be compared, a simple computation performed at the end of the demonstration.

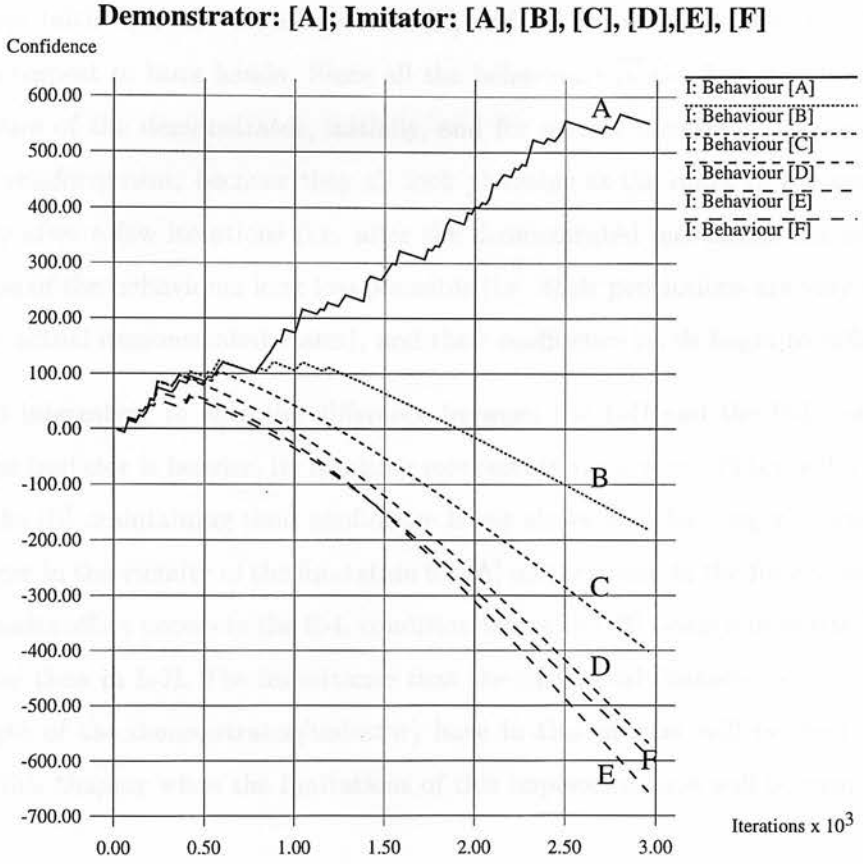

Figure 4.7: Confidences of imitator's internal behaviours [A-F] when demonstrator executes behaviour [A]; L-H condition

Figures 4.6, 4.7, and 4.8, show the confidence values of each of the experimental conditions, L-L/H-H[6], L-H, and H-L. In all three figures all the imitator's behaviours start initially by having the same confidence, zero, and end up having a confidence correlated with their similarity to the demonstrated behaviour. Since the demonstrator is demonstrating the movement towards reaching the letter [A][7], the imitator's [A] behaviour gets the highest confidence, well above zero. All the other behaviours end up well below zero. It is interesting to note that while clearly none of them have done well,

[6] L-L and H-H conditions produce the same results; L-L is shown.

[7] From now on, only the letter that corresponds to the posture that is to be achieved will be used to represent movement from the rest position to that posture.

some have done better than others. For example, [B] which is more similar to [A] than the others (only differs from [A] by forty-five degrees on the right hand) has a higher confidence (although still negative) than [E] and [F] for example, which differ from [A] with respect to both hands. Since all the behaviours in the first iteration assume the posture of the demonstrator, initially, and for several iterations, they all receive positive reinforcement, because they all look plausible at the onset of the movement. It is only after a few iterations (i.e. after the demonstrated movement has advanced) that some of the behaviours look less plausible (i.e. their predictions are very different from the actual demonstrated states), and their confidence levels begin to reflect that.

It is also interesting to note the difference between the L-H and the H-L conditions. When the imitator is heavier, its resulting movements are slower. This results in behaviours like [B] maintaining their confidence levels above zero for longer, because they stay longer in the vicinity of the final state for [A] on their way to the final state for [B]. The opposite effect occurs in the H-L condition where the [B] behaviour starts descending earlier than in L-H. The importance that the dynamical characteristics (including the weight of the demonstrator/imitator) have in this process will be demonstrated later in this chapter when the limitations of this implementation will be examined.

Sequences of actions

In this set of experiments, the demonstrator is executing behaviours that correspond to 'words'. Behaviours start from the rest position, and move sequentially through the postures that correspond to each of the letters of the word (without returning to the rest position after each letter). Similarly to the single-movement experiments, all the words of the imitator start from a confidence of zero, and end-up at a confidence level dependent on their level of similarity with [Cooler], the demonstrated word. [Cool], [Cook], [Coot] and [Cookie] are clearly rejected under all experimental conditions, while [Cooler] always achieves the best confidence, with [Cooker] being the second best due to its high similarity (only one letter different).

It is also interesting to observe the confidence graphs with respect to their behaviour over time. All of the behaviours have [coo] as the first three letters, so all of them have positive confidence while the demonstrator executes the [coo] part. Immediately after

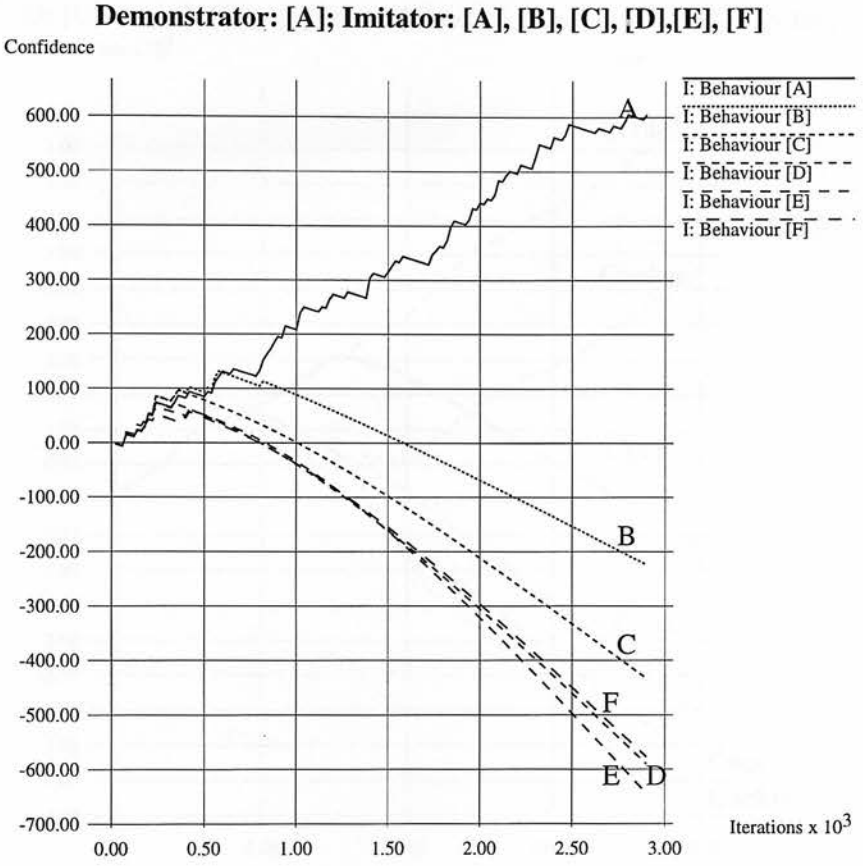

Figure 4.8: Confidences of imitator's internal behaviours [A-F] when demonstrator executes behaviour [A]; H-L condition

that, [cookie], [cooker], [cook] and [coot] begin their descent while [cool] joins right after the demonstration of the next letter [L] is also completed. It is also interesting to note that [cooker] begins to regain some of its confidence , after the [K] has been completed and [er] is being demonstrated.

Limitations

A final set of experiments demonstrates the limitations of this implementation: in figure 4.12 the demonstrator is executing a behaviour that the imitator does have in its repertoire ([cooler]); however this time the imitator is 400% heavier than the

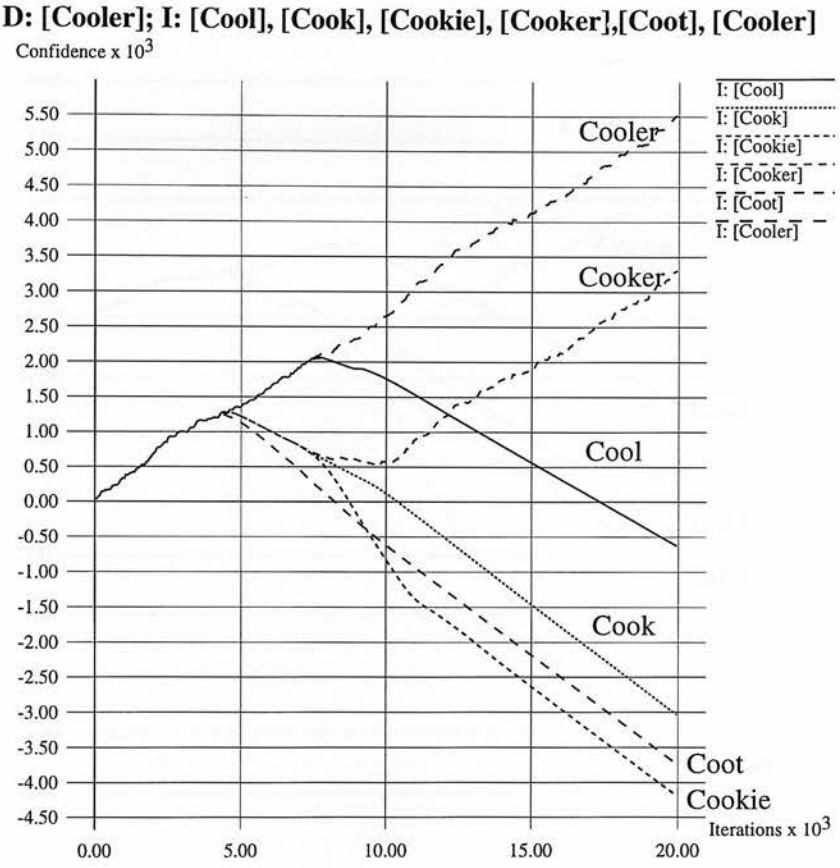

Figure 4.9: Confidences of imitator's internal [Coo*] behaviours when demonstrator executes behaviour [Cooler]; L-L/H-H condition

demonstrator, so it is not capable of executing the demonstrated behaviour at the demonstrator's speed levels. As a result, all the behaviours end up with very low (below zero) confidence values.

Figure 4.13 demonstrates the importance of limiting the adaptation of the gains within upper and lower bounds. In this experiment, the previous experiment was repeated but this time the gains were allowed to change without restrictions. As a result of the different dynamics, the architecture tried to compensate for the prediction errors by substantially increasing the gain parameters, but the plant was destabilized and the resulting confidence levels were even worse than the ones achieved with limited

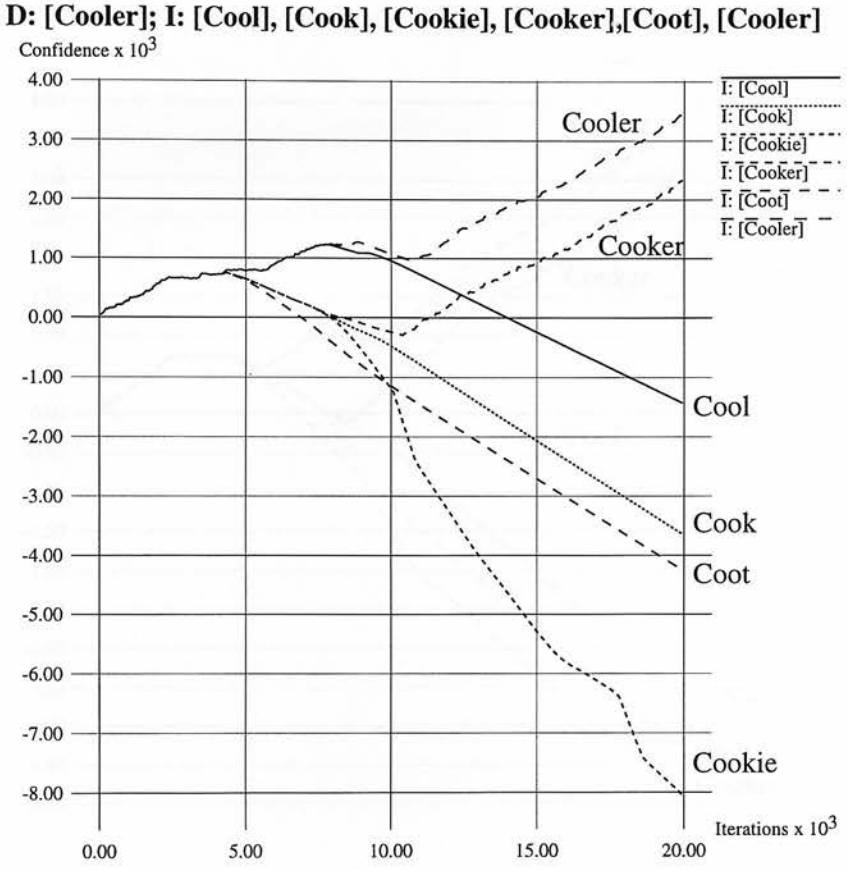

Figure 4.10: Confidences of imitator's internal [Coo*] behaviours when demonstrator executes behaviour [Cooler]; L-H condition

adaptation.

4.5 Discussion

The active imitation architecture described in this chapter has certain advantages and disadvantages. This section's aim is to discuss these.

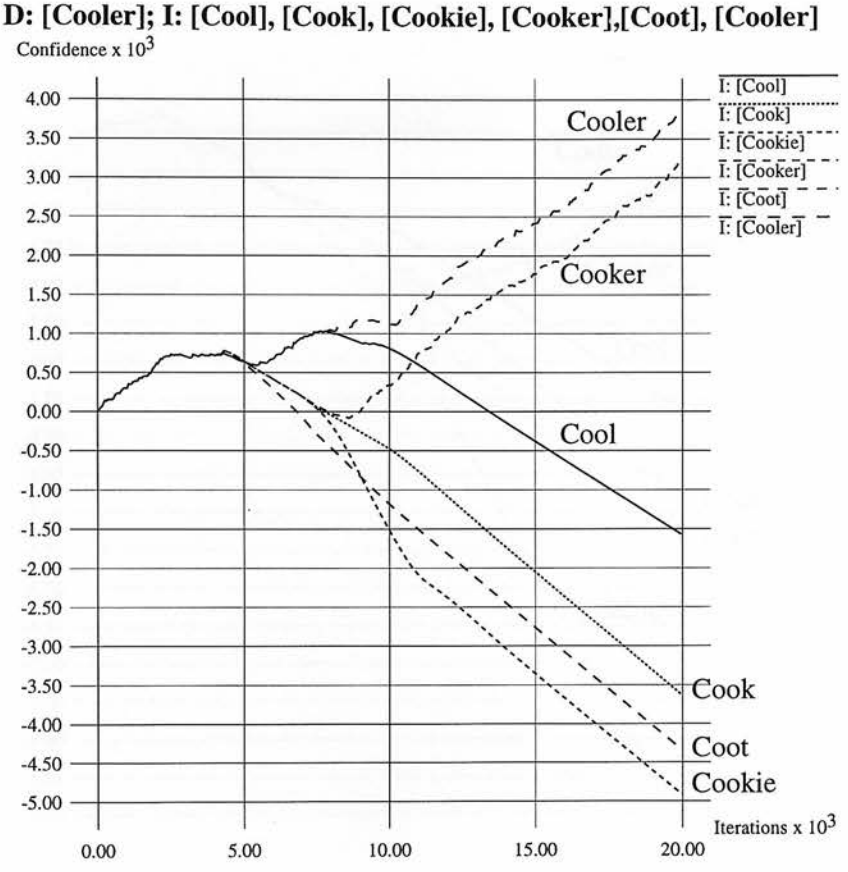

Figure 4.11: Confidences of imitator's internal [Coo*] behaviours when demonstrator executes behaviour [Cooler]; H-L condition

4.5.1 Advantages

The architecture described has three major advantages: agreement with biological data available on imitation mechanisms, inherent parallelism, and principled treatment of two imitation related problems, i.e. when to initiate learning algorithms, and how to determine the quality of a match between demonstrated and internal actions. The discussion on the agreement between the characteristics of this architecture and of biological data is deferred until chapter 6; the two other advantages are described below.

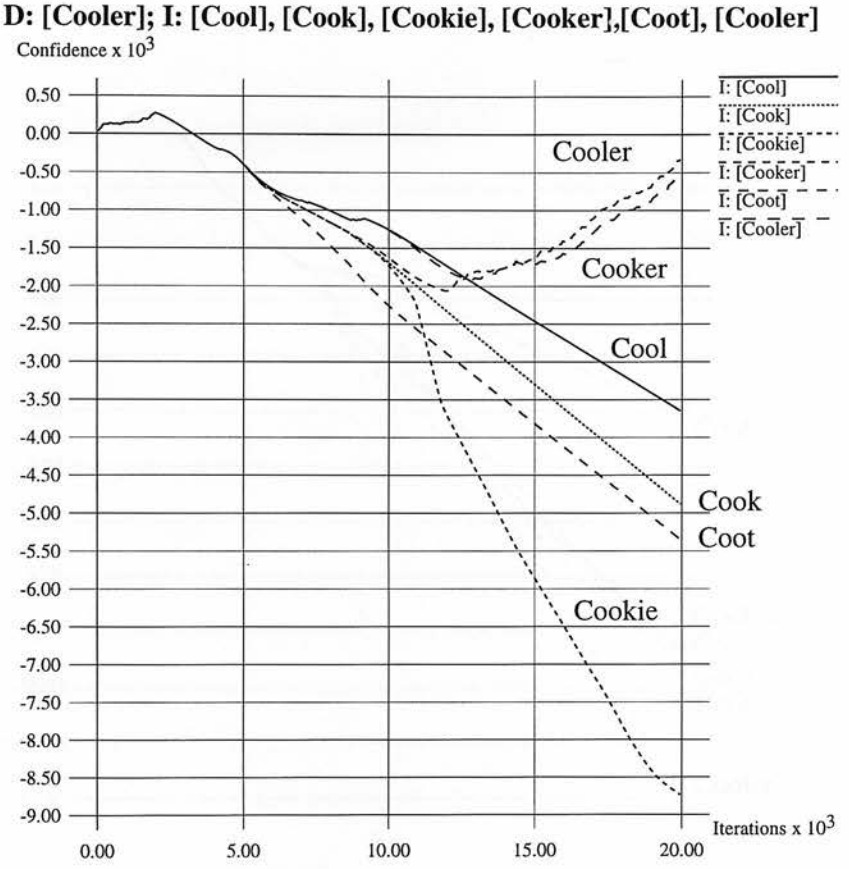

Figure 4.12: Confidences of imitator's internal [Coo*] behaviours when demonstrator executes behaviour [Cooler]; Imitator is 400% more heavy than demonstrator

The architecture described is fundamentally parallel in nature. Each behaviour obtains a copy of the input data and handles on its own the generation of motor commands, prediction, error signal and inhibition/reward values. This means that new behaviours can be added easily in this framework without disturbing the current ones.

In addition, the architecture offers a principled way of dealing with two important problems in imitation learning:

- How to determine the quality of match between demonstrated and internal behaviours.

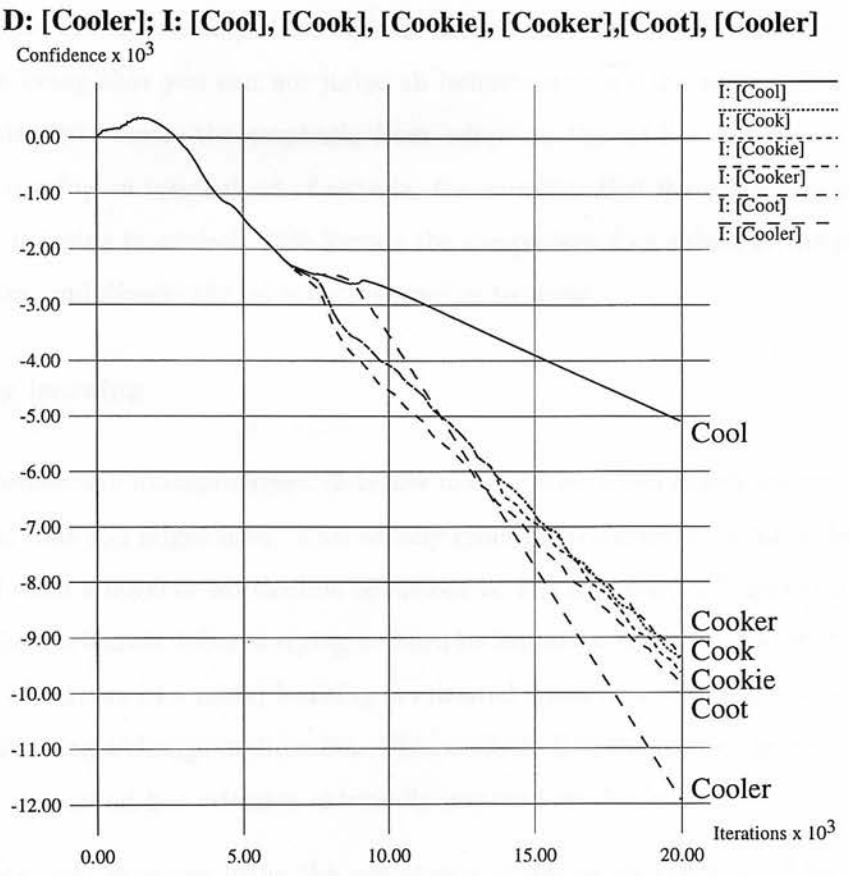

Figure 4.13: Confidences of imitator's internal [Coo*] behaviours when demonstrator executes behaviour [Cooler]; Imitator is 400% more heavy than demonstrator, and adaptation safety boundaries have been removed

- When to initiate learning of new behaviours.

Determining the quality of the match

One of the problems in imitation research is determining how well the imitated (internally or externally) behaviour matches the demonstrated behaviour (Nehaniv and Dautenhahn, 1998).

This can be demonstrated by taking a tennis serve as an example task: is the quality of the match to be based on the trajectory of the arm, the trajectory of the tennis ball,

or whether it achieved the task of sending the ball to the opposite court (and so on)? Writing an evaluation formula given the criteria for comparison is not a major problem. The problem lies in *selecting* these criteria according to the different situations, the point here being that you can not judge all behaviours with the same set of criteria. This architecture shifts the emphasis from adopting the ad-hoc criteria of a third observer to using an internal set of criteria, *the variables that the internally generated behaviour is trying to control.* This focuses the comparison to a subset of the perceived information, and directs the imitator's attention to these.

Initiating learning

Another problem in imitation research is how to determine when to initiate any learning algorithms that you might have. This usually relies on arbitrary or domain-dependent criteria of what a novel or worthwhile behaviour is. For example, in Hayes and Demiris (1994), where a learner robot is trying to learn by imitation how to negotiate the different types of corners in a maze, learning is initiated when a 'novel' event occurs, novel in this case being a change in direction. This works well in the particular configuration used, but it is an ad-hoc criterion externally imposed on the learner.

The architecture proposes using the confidence values as an initiator of learning. If none of the behaviours that the imitator has in its repertoire managed to achieve positive (or above a certain threshold) value, the demonstrated behaviour is novel and the learning algorithms should be initiated in order to acquire this behaviour. The next chapter is a demonstration of this.

4.5.2 Disadvantages

The architecture described earlier relies on having accurate forward models. If the models are not accurate, even the right imitator's behaviours will be deemed inappropriate since the generated predictions will be wrong. Although this disadvantage did not produce any problems in the experiments reported in this chapter, in other situations it might do, in which case it can be avoided by comparing the forward model's prediction of a command's outcome with the actual outcome of executing that command, and using the error signal to improve the forward model. It has been shown that

forward models can improve simultaneously with the behaviours (or inverse models) that they are connected to, while performing a task (Jordan and Rumelhart, 1992).

4.6 Summary/What next

In this chapter, a distributed architecture, based on paired behaviour-forward model structures operating in parallel, was described, and experiments implementing it on a dynamics simulator of a thirteen DoF robot were presented. It was demonstrated how such an architecture can be used to generate an action as well as perceiving it when generated by others.

The architecture described only considered the cases where the demonstrated action or sequence of actions were already in the imitator's repertoire. If the demonstrated action is not in the imitator's set of known actions, it will neither be recognised or imitated. The next chapter deals with these cases, by blending the active imitation architecture of this chapter, with the passive one of the previous chapter, with the final dual-route architecture able to imitate and learn novel behaviours.

Chapter 5

Imitating and Learning Novel Behaviours

5.1 Introduction

The architecture in the previous chapter can deal with the recognition and imitation of demonstrated movements already in the imitator's repertoire. This chapter will deal with the situations where the imitator does not know how to perform the demonstrated movements, or only knows various parts of it but not the complete sequence. In essence, this chapter combines the passive and active approaches described in the previous chapters, in what will be a *dual-route* imitation architecture. First, the case of completely unknown movement will be considered, followed by two cases of "sequence" learning; one where all the parts are known and the learning of the sequence is required, and one where some of the parts are known but not all of them.

5.2 Incorporating learning

In the experiments described in the previous chapter, the demonstrator does not perform any movements that are not already in the imitator's repertoire. One of the imitator's behaviours always ends up having positive confidence and is selected as the one to be imitated. However, if the demonstrator performs a behaviour that the imitator does not know, all behaviours end up with negative or zero confidence and none of them is judged as suitable for imitation. As was briefly mentioned in the discussion section of the previous chapter, this can be used as a trigger condition in order to

attempt to learn[1] the demonstrated behaviour.

The solution that is proposed in this chapter is to use the passive architecture of chapter 3 in order to imitate any movements not already in the imitator's repertoire. Figure 5.1 demonstrates this at the high level.

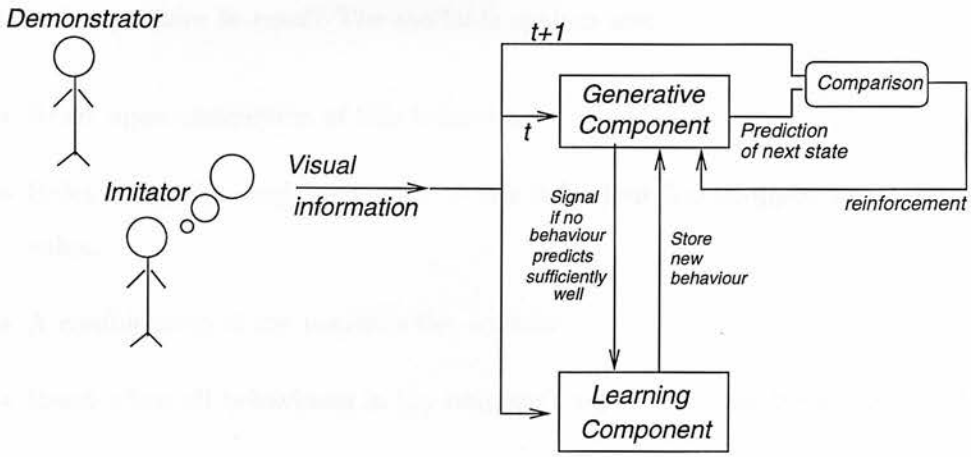

Figure 5.1: Combining the passive and the active imitation architectures

The representative postures that are extracted during the unknown demonstrated behaviour are stored, and together with a PID controller, form new behaviours which are added to the imitator's set. If the demonstrated behaviour consists of more than one movement (if it is a 'word'), the situation is complicated by the fact that behaviours, apart from being either completely known or unknown, can also contain known parts (for example some letters might be known, while some others might not), in which case what is required is the learning of the sequence, utilising the pre-existing representation for the already known parts rather than learning them from scratch. All these cases are examined in the experimental section that follows.

The fact that a behaviour that is already present in the imitator's repertoire might appear (at any point during the demonstration) as part of the demonstrated sequence requires the existence of a mechanism that reinitialises (resets) the imitator's behaviour

[1] In this chapter, learning is the process of acquiring a behaviour, either its trajectory specifications or the motor commands needed to achieve it. Learning as used here does not imply generalisation or adaptation to different circumstances or any other processes as used in the field of machine learning (Shavlik and Dietterich, 1990).

during the demonstration[2], so even if the behaviour has a low confidence because it didn't match well previous parts of the demonstrated sequence, it will be given a new chance for the current part.

The crucial issue here is, during the demonstration, *when should a behaviour in the imitator's repertoire be reset?* The available options are:

- Reset upon completion of this behaviour.
- Reset when the confidence level of this behaviour has dropped below a certain value.
- A combination of the previous two options
- Reset when all behaviours in the imitator's repertoire have been completed.

The experimental results in the next section will demonstrate that the best results were obtained by the last option, i.e. resetting when all the behaviours in the imitator's repertoire have been completed.

A related issue, which becomes particularly important in the last (and selected) option is *what happens to the confidence values of the behaviour if it is completed but is not required to be reset until some point later?* The options available are:

- The confidence drops immediately to zero when the behaviour is completed.
- The confidence value retains its final value until the behaviour is reset.
- The confidence adjustment formula is still applicable even after the completion of the behaviour, which means that further confidence changes are dependent on the difference between the behaviour's final state and the demonstrator's current state.

For reasons that will be explained in the next section, the second option was selected.

[2] Resetting involves re-running the initialisation steps that each behaviour takes at the start of the experiment, i.e. the state of the behaviour is set to that of the demonstrator, its confidence is set to zero, and the behaviour starts moving towards its first (or only) goal.

5.3 Experiments

In this section, the results of applying the hybrid active-passive architecture in three possible cases are presented: the imitator observing a completely unknown movement sequence, a sequence with all of its parts known to the imitator, and a sequence with both known and novel parts. The methodology that has been adopted here in order to describe the behaviour of the architecture is to demonstrate the unknown (or partially known) movement to the imitator, record the confidence values of the imitator's behaviours, and allow the imitator to attempt to acquire the demonstrated sequence. Then, the experiment is repeated with the acquired behaviour being part of the imitator's repertoire, and the confidence values of the imitator's behaviours are again recorded during the demonstration. Graphs are displayed depicting the confidence values of the behaviours in the imitator's repertoire before and after the acquisition.

5.3.1 Completely unknown movement

This set of experiments examines the cases which involve the demonstrator executing a behaviour completely unknown to the imitator. Figure 5.2 shows the confidences plot of the imitator's behaviours [A-F] while the demonstrator executes [G]. Naturally, all of imitator's behaviours end up with a negative confidence value; concurrently with the internal execution of candidate behaviours, the passive route was extracting the representative postures of the demonstrated movement. Since none of the behaviours performed adequately during the demonstration, the extracted representative postures, together with a PID controller, formed a new behaviour which was added to the imitator's repertoire. The experiment is now repeated with the imitator equipped with the [learned-G] behaviour. Figure 5.3 shows the confidences plot of the imitator's internal behaviours while the demonstrator executes [G], where [learned-G] does end up with positive confidence. Figures 5.4 and 5.5 demonstrate the application of the architecture in a sequence of two movements: the demonstrator executes [CA], and the imitator is not capable of imitating it (figure 5.4) until the representative postures have been extracted and the new behaviour has been added to the imitator's repertoire (figure 5.5).

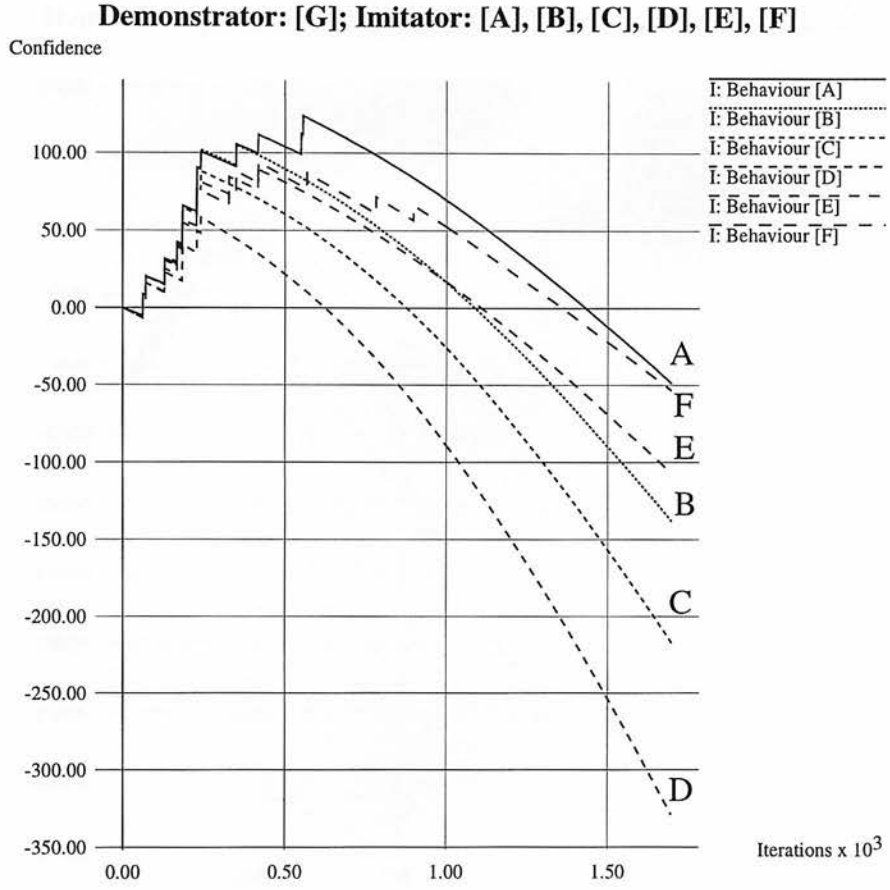

Figure 5.2: The confidences plot before learning: demonstrator executes [G] while imitator does not have that behaviour in its repertoire

5.3.2 All parts known

This set of experiments demonstrates the cases which involve the demonstrator executing a behaviour which is not known to the imitator (as a sequence), but is composed of known parts. Since a known behaviour can appear as part of the demonstration at any point, there is a need for a mechanism for resetting behaviours, so they can still detect occurrences of themselves in the demonstrated sequence, even if they don't come right at the start of the demonstration. The interesting problem that is posed here is *when should a behaviour reset itself* (and essentially "try again")? Four different

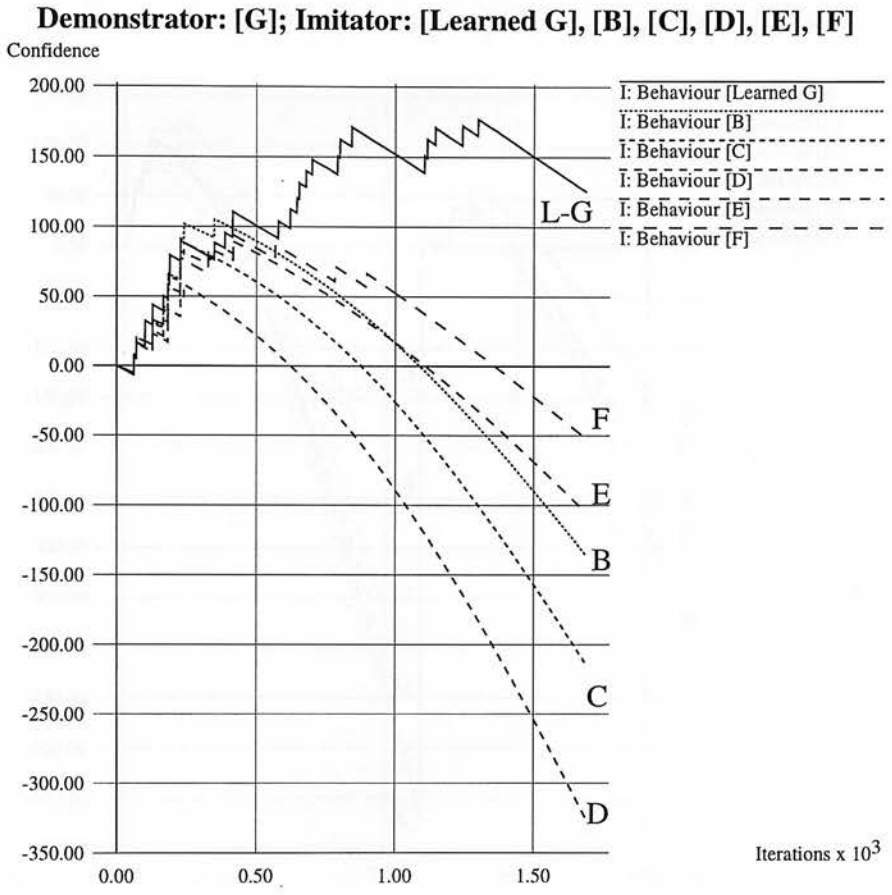

Figure 5.3: The confidences plot after learning: demonstrator executes [G] with imitator having the learned behaviour [L-G] in its repertoire

conditions were tested: resetting a behaviour when its confidence falls below a certain level (example: figure 5.6), resetting each behaviour when it is completed (example: figure 5.7), combining these two options (example: figure 5.8), and resetting each behaviour when all the behaviours have been completed (example: figure 5.9). The final option was selected since it provides more clear information for selecting behaviours than the other three. The first option (figure 5.6) has the disadvantage that since it is based on confidence levels, the first behaviour that does well will remain active throughout the remainder of the demonstration. The second option (figure 5.7) has the disadvantage that it does not provide a clear point where the confidence levels can be

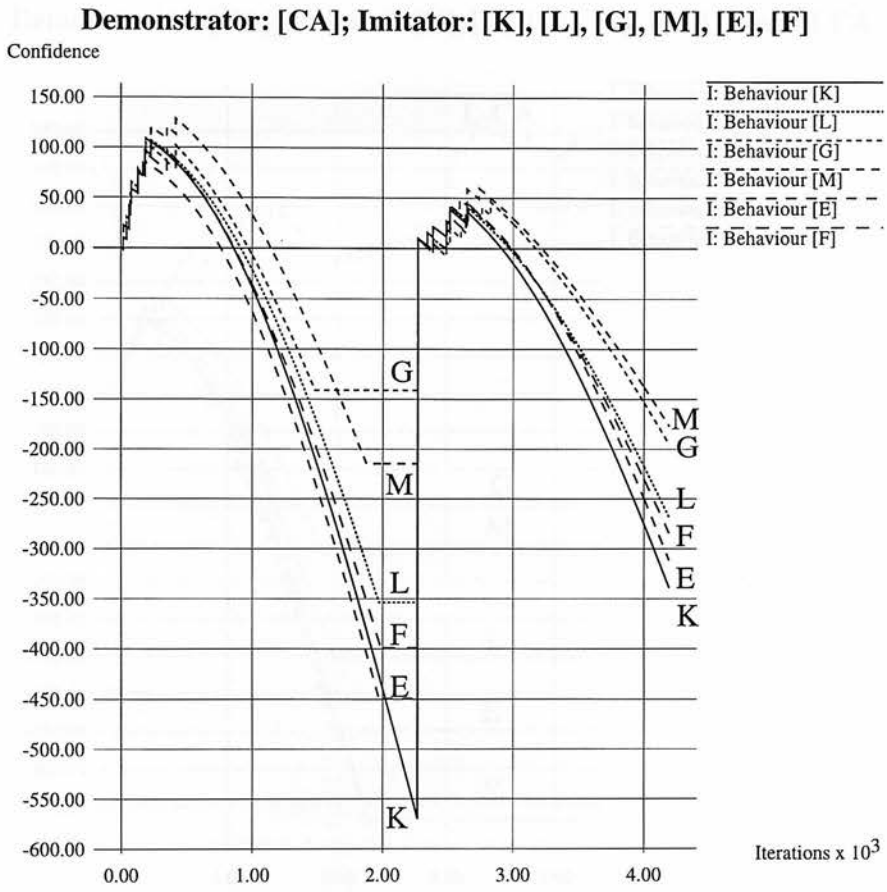

Figure 5.4: The confidences plot before learning: demonstrator executes [CA] but imitator does not know this behaviour

compared in order to select a winner behaviour. Combining the two does solve the first problem, but worsens the second (figure 5.8). On the contrary, resetting behaviours in a coordinated manner, when all of them are completed overcomes both problems (figure 5.9): behaviours will achieve high confidence levels only during the presentation of a relevant part of the demonstrated sequence, and comparison of confidence levels can occur right before the coordinated resetting. Figure 5.9 illustrates this: the demonstrator executes [Cut] while the imitator has [U, L, C, E, F, T] in its repertoire. The first segment of the demonstration is successfully recognised as [C], and so are the remaining [U] and [T] parts. The sequence is learned by simply concatenating the

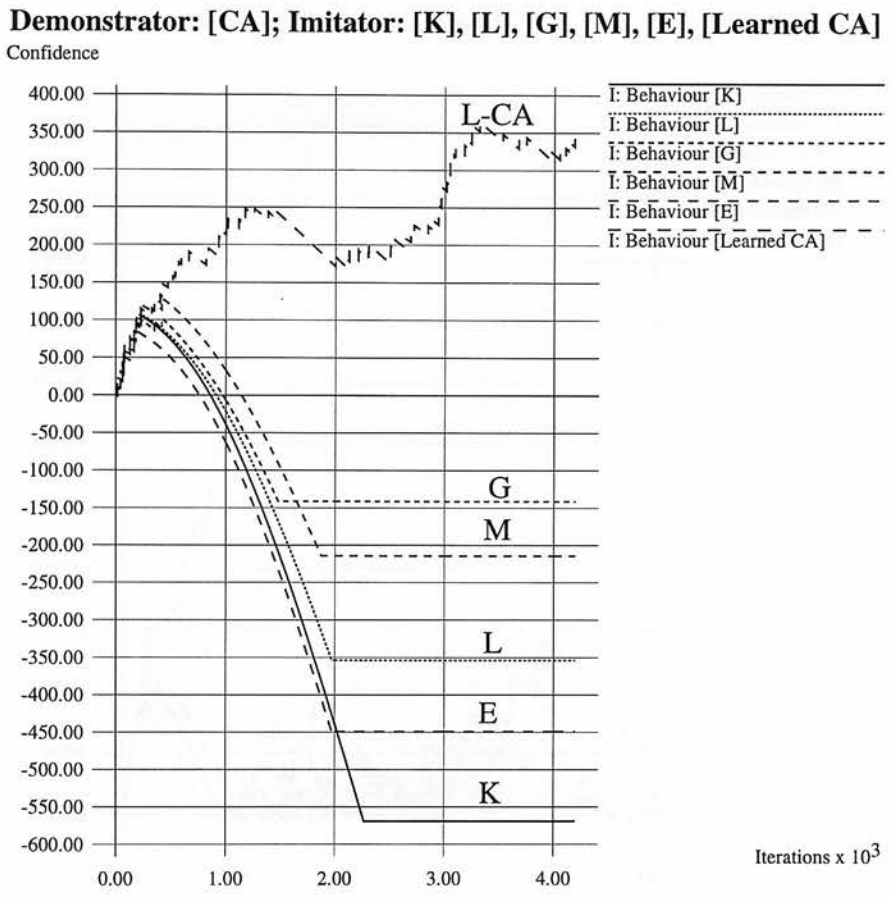

Figure 5.5: The confidences plot after learning: demonstrator executes [CA] with imitator having the learned behaviour [L-CA] in its repertoire

already known [C], [U], [T] behaviours.

Another question that needs to be answered is *what happens to the confidence of a behaviour after it is completed, but is not yet required to be reset?* As mentioned earlier, the confidence can either be set to zero, retain its final value, or remain dependent on the difference between its (constant) state (the final state achieved) and the current demonstrated state. The first one was rejected since it complicates the task of selecting between behaviours by immediately resetting the confidence value of a behaviour to zero when it is completed. A simple selection based on the final values is no longer

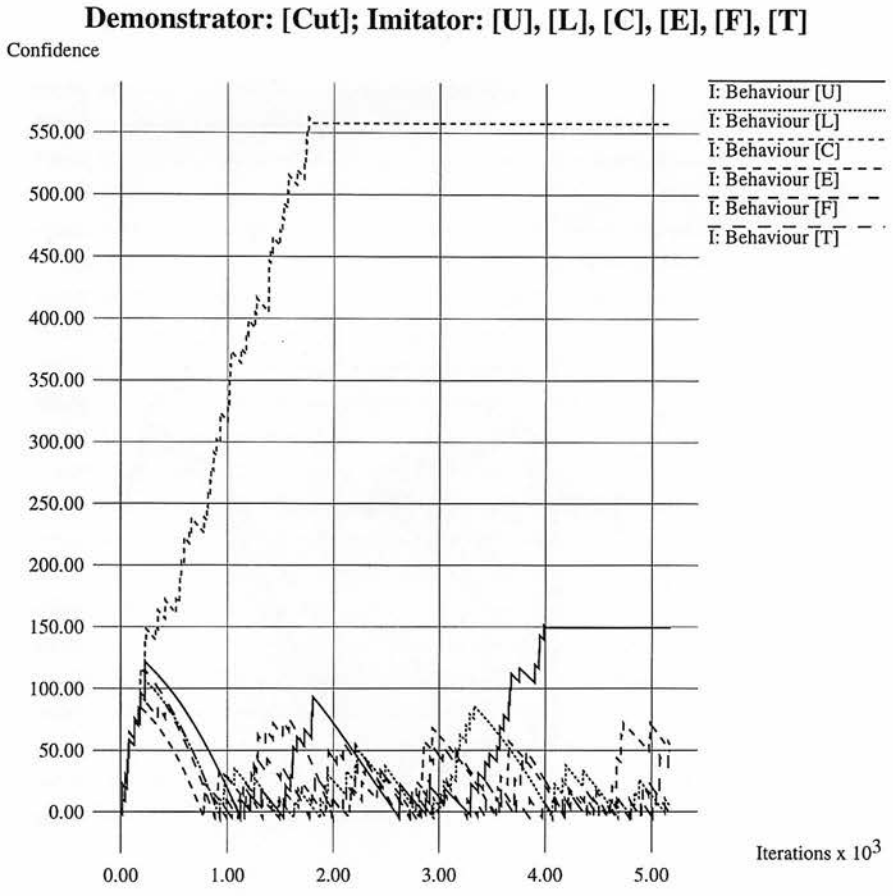

Figure 5.6: Resetting each behaviour when its confidence falls below a certain level

possible, unless a record of the final values achieved by each behaviour is kept[3]. The third one was rejected because it essentially amounts to punishing a behaviour for the errors in predictions that occurred while waiting for other behaviours to be completed. So, the second one was selected and used in the experiments reported here.

[3] If a record of the final values is kept, and the comparison is based on these final values, options one and two are functionally equivalent.

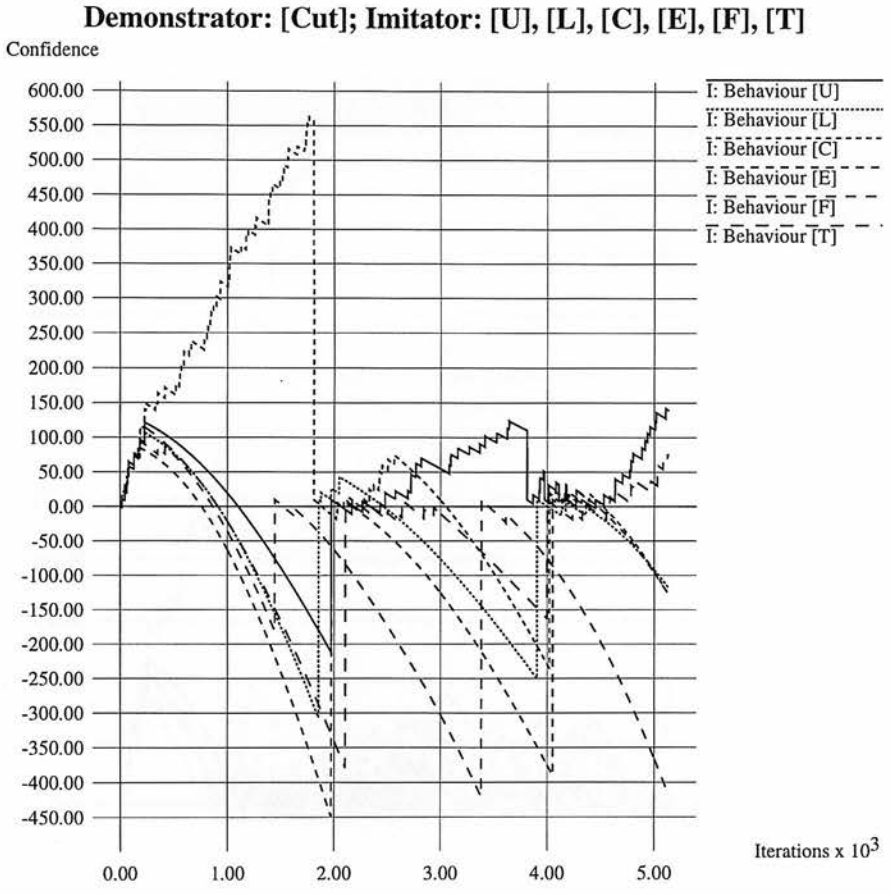

Figure 5.7: Resetting each behaviour when it is completed

5.3.3 Some parts known

This section examines the cases where parts of the demonstration are known to the imitator, but not all of them. The architecture deals with such cases by utilising the existing representation of a behaviour when this behaviour achieves high, positive confidence levels, while utilising the extracted representative postures for the parts that are not recognised. Example figure 5.10 illustrates this: the demonstrator executes [Cut] with the imitator having behaviours [C, L , G, E, F, T], i.e. the [U] part is unknown. As expected, after recognising the [C] part, the imitator fails to recognise the [U] part, and subsequently is successful in recognising the [T] part. Representat-

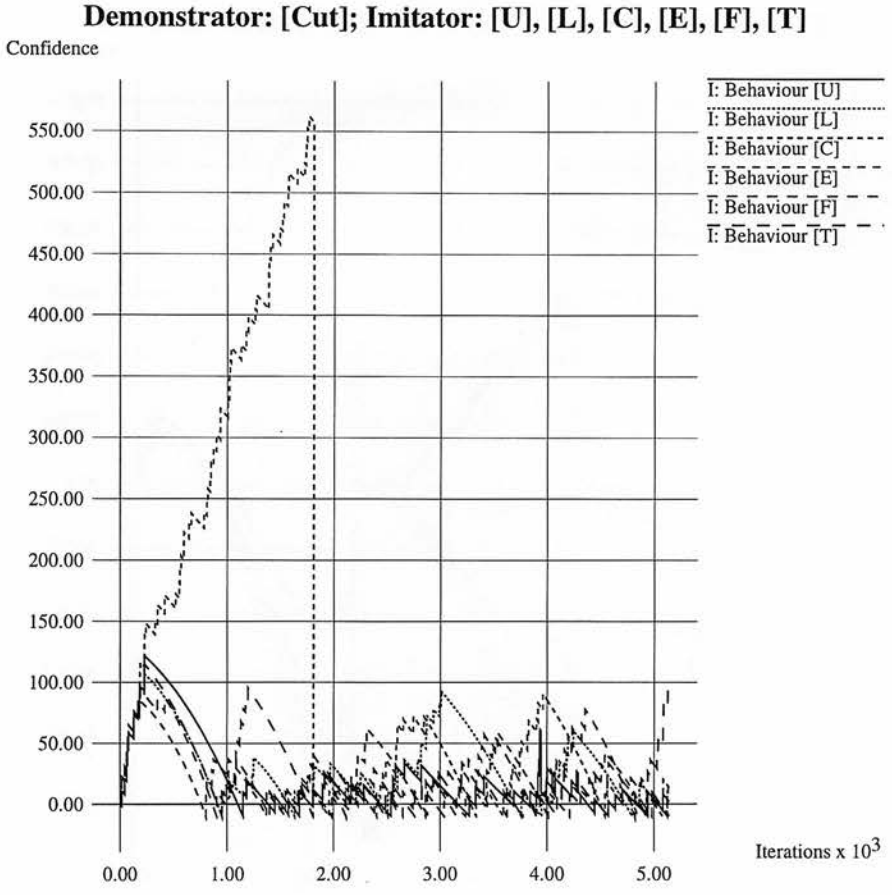

Figure 5.8: The previous two conditions combined: Resetting each behaviour when its confidence falls below a certain level or when it is finished

ive postures extracted during the presentation of the [U] part are concatenated with existing representations for the [C] and [T] parts, and the resulting behaviour achieves high positive confidence when the experiment is re-run with the new behaviour in place (figure 5.11).

5.4 Discussion

As demonstrated by the experiments in the previous section, the architecture resulting from the combination of the passive and active routes described in chapters 3 and

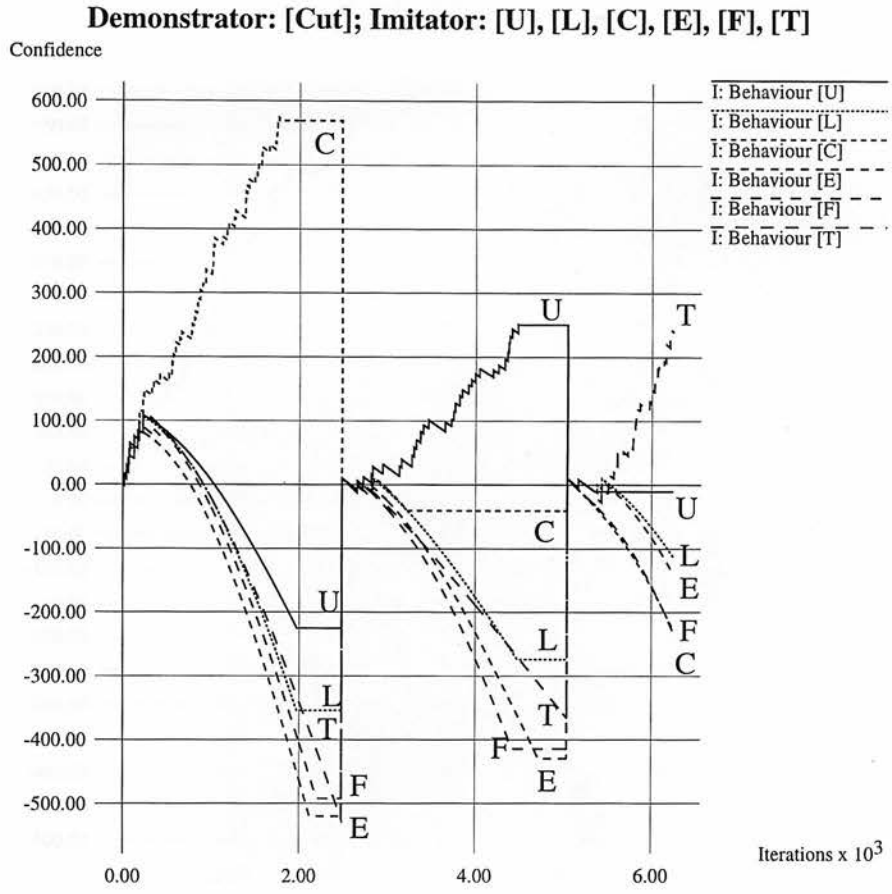

Figure 5.9: The confidence plots of behaviours [U, L, C, E, F, T] while demonstrator executes [Cut] - resetting each behaviour when all behaviours are completed

4, has several desirable capabilities: it can learn behaviours from scratch (figures 5.3 and 5.5), concatenate existing behaviours to form sequences (figure 5.11), and is capable of filling the gaps for sequences that are only partially known, using existing representations for the known parts, and extracted ones for the unknown.

Comparing figures 4.6 with 5.3, and figures 4.9 with 5.5 reveals a clear difference between the levels of confidence that predefined representations of a behaviour reach and the ones reached by the learned representations. Pre-defined representations have a much higher final confidence value than the learned ones for the same movement.

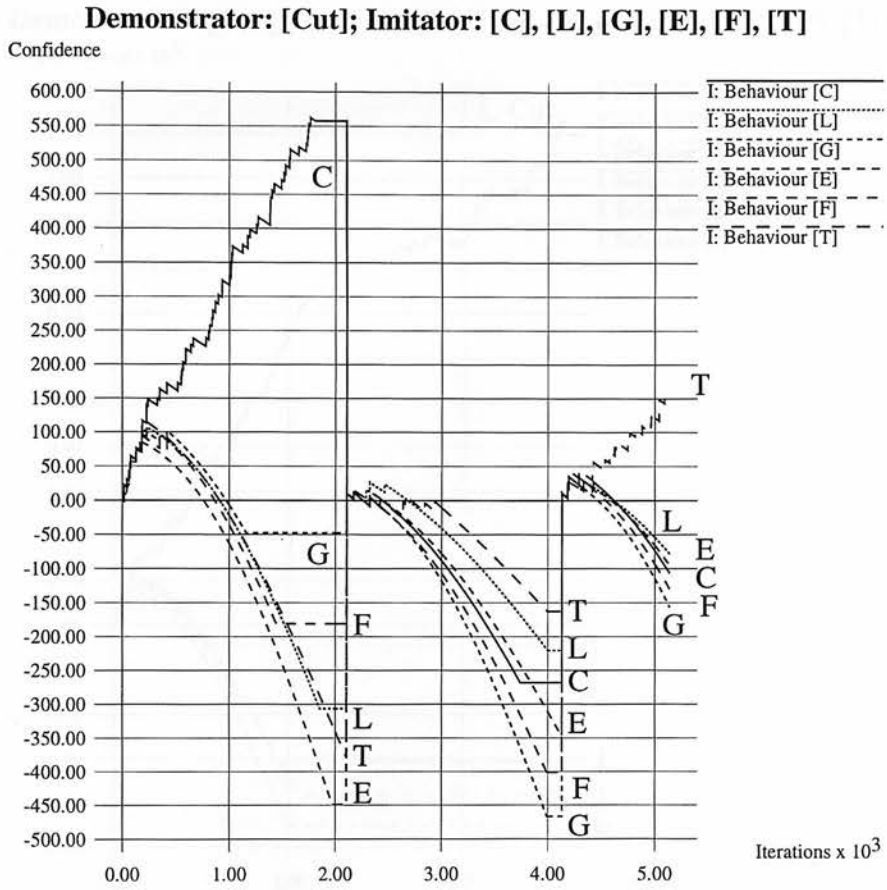

Figure 5.10: The confidence plots of behaviours [C, L, G, E, F, T] while demonstrator executes [Cut]

This is due to the fact that when the experiment is performed with the predefined representations, the demonstrator and the imitator are attempting to achieve the same set of goals (as defined precisely by the ISSC specifications). In the learned case, the demonstrator still attempts to achieve the predefined goals, but the imitator is now attempting to achieve the goals that were extracted through the passive route, which is mediated through imprecise perception. The noisy representations extracted are good enough to ensure recognition of the demonstrated movements that they correspond to, but not to reach the same performance as the formal ones.

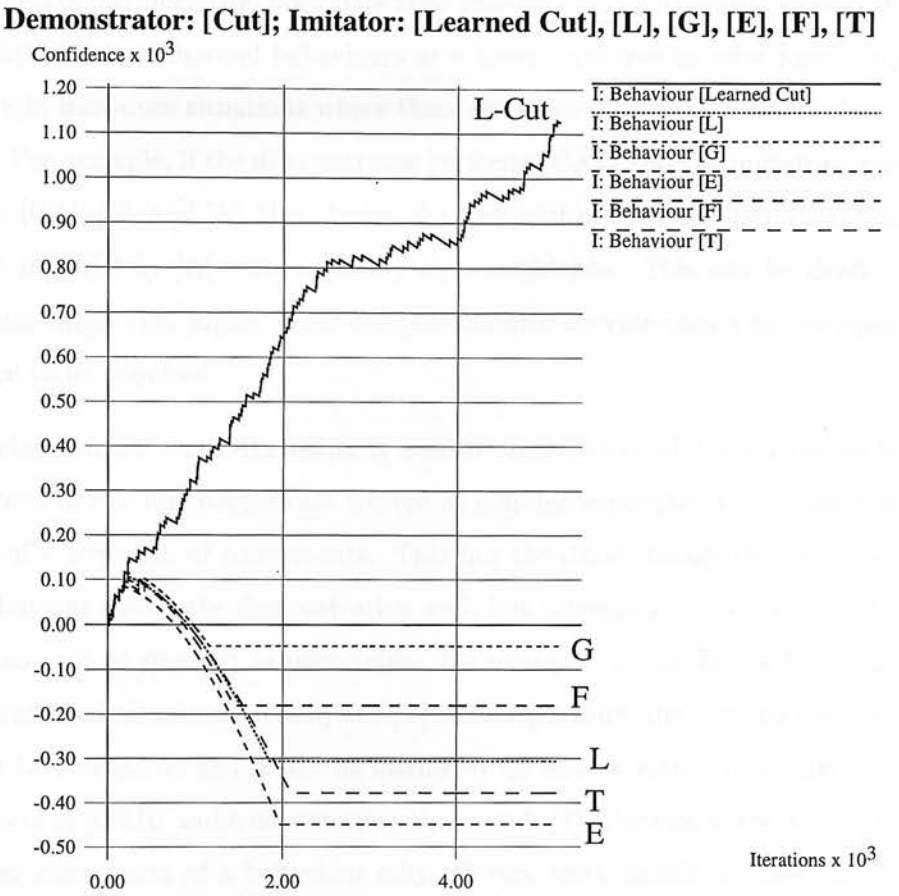

Figure 5.11: The confidence plots of behaviours [L, C, E, F, T], and of learned behaviour [L-Cut] while demonstrator executes [Cut]

One disadvantage of this architecture, in its current form, is that the coordinated resetting introduced in this chapter means that behaviours are no longer independent from each other, and the number (and characteristics) of the behaviours in the imitator's repertoire have an influence on the performance of the architecture. Each behaviour (irrespective of the number of components it has) influences the performance of all other behaviours by playing a role on the timing of their resetting. This might lead to an undesirable situation where a longer but incorrect behaviour might delay the resetting of other behaviours so that they miss demonstration intervals where they might be applicable. This could be solved by organising the behaviours in a more hierarchical

manner, with more complex and long sequences at the top level and more basic and short ones at the bottom. Then the architecture can be adapted such that behaviours at one level of the hierarchy coordinate their resetting only with behaviours at the same level while leaving (shorter) behaviours at a lower level free to reset more frequently. This might introduce situations where there are more than one suitable behaviours at a time. For example, if the demonstrator performs [CAT] and the imitator's repertoire includes [CA], [C], and [A], then during the first part of the demonstration, both [CA] and [C] followed by [A] will be having high confidence. This can be dealt with by preferring longer (i.e. higher level) components over shorter ones when composing the sequence to be acquired.

On a related note, some discussion is needed on the issue of "behaviour as a unit". Behaviours in this architecture are treated as non-decomposable units, even when they consist of a sequence of components. This has the disadvantage that if earlier parts of a behaviour match the demonstration well, but subsequent parts do not, the whole behaviour will be rejected as unsuitable. For example, if the demonstrator performs [CAT] and the imitator has [CAR] and [T] in its repertoire, the demonstrated sequence will not be recognised and it will be learned from scratch rather than taking the first two letters of [CAR] and concatenating them with [T]. Currently, there isn't any way to utilise some parts of a behaviour only. Future work should address this issue by incorporating the ability to decompose behaviours into their constituent parts. Even the single letter behaviours, currently used as the basic set, can be decomposed into more primitive movements, for example, splitting them into the right and left arm components. This quest towards 'motor primitives' underlying all behaviours is an important issue in motor control since it simplifies the complexity involved in the control of articulated movement. Several proposals have been put forward including programmable pattern generators based on non-linear attractor dynamics (Schaal and Sternad, 1998), postural primitives (Williamson, 1996) inspired by those observed in frogs and rats (Bizzi et al., 1991; Giszter et al., 1993), behaviour-based primitives (Mataric et al., 1998a; Demiris and Mataric, 1998) and non-linear force fields (Mussa-Ivaldi, 1997), among others.

Chapter 6

A model of primate imitation mechanisms

In the previous chapters, two imitation architectures were presented, a passive and an active one, and a hybrid combination of them was subsequently developed. In this chapter, the biological plausibility of the combined dual-route architecture will be examined by proposing it as a model of primate action imitation mechanisms. First, a set of criteria that a model must meet in order to be useful will be presented, followed by an analysis of the model based on these criteria.

6.1 On criteria for useful models

Despite extensive use in the Artificial Intelligence, Cognitive Science and Artificial Life fields of the word "model", there are surprisingly few attempts to develop a set of criteria with respect to what a proper and useful model should be like (notable exceptions, frequently from scientists in other fields, include (Lehman, 1977; Rothenberg, 1989; Webb, 1993). By considering programs as the computational embodiments of a theory of how the modelled system might work, a substantial amount of theoretical work from the philosophy of science literature (e.g. Popper, 1972) on the possible criteria concerning the adequacy and proper form of a theory can be useful here. Having as a primary target the development of useful models, the following criteria were set for use in this thesis:

- A model should be clear on what it is a model *of*, and at what level of description.

This allows the incorporation of a number of pieces of evidence regarding the structure and behaviour of the modelled system as test sets for the plausibility of the model. A model should be accurate with respect to this evidence. The degree of accuracy, and the range of evidence that it agrees with can be used as a measure of the generality of the model.

- By virtue of being designed as an analog of the modelled system, a model should provide possible explanations for the data available about the modelled system.
- A model should be able to generate testable predictions. This is considered important in order to establish the scientific usefulness of the model, and demarcate it from useless exercises in computer programming.

The rest of the chapter is organised around these criteria. The following three sections present the validation data, the explanations and the predictions respectively.

6.2 The architecture as a model of primate imitation mechanisms

The first criterion of the ones described earlier requires an explicit statement on what the architecture is a model *of*. The aim of this section is to propose the architecture described in chapter 5 as a model of primate imitation mechanisms, and describe evidence from imitation research in primates that can be used as test sets for the plausibility of the model.

6.2.1 Why primate?

Why specifically target primates? The main reason for this is that, in contrast to "lower" animals where the majority of research has concentrated on whether a certain animal is capable of imitation or not (chapter 2), there is a sufficient amount of data with respect to the *underlying mechanisms* of primate imitation to make a computational model possible.

6.2.2 The validation data

This section presents neurophysiological, psychological and brain activation data pertaining to issues important to the approach adopted in this thesis. Firstly, human brain activation data are presented, followed by neurophysiological data on "mirror neurons" found in the premotor areas of the monkey brain. Since this thesis advocates imitation as a repetition of an earlier (internally performed) generative process, psychological data on working memory for movements are presented. The interplay between observing, imagining, performing and imitating a movement is the unifying theme of the psychophysical data presented right after, and the presentation of the validation data is concluded with the examination of data available on human imitation capabilities following brain damage, focusing on resulting apraxia disorders.

Activation of brain structures in humans

In humans, several experiments have investigated the interplay between action generation and action perception (Demiris and Hayes, 1999). Fadiga et al. (1995) stimulated the motor cortex of human observers and recorded the motor evoked potentials (MEPs) from hand muscles, utilising the assumption that if action observation activates the premotor cortex (as it does in monkeys), this activation should induce an increase of the motor evoked potentials elicited by the magnetic stimulation of the motor cortex. They found a significant increase of the MEPs when subjects observed movements, and additionally the patterns of muscle activation was very similar to the pattern of muscle contraction present during the execution of the same action, i.e. the increase was present only in those muscles that are active when the human subjects executed these actions.

A different set of experiments with human subjects used Positron Emission Tomography (PET) brain scanning as a way of mapping the brain regions whose activations are associated with the observation of hand actions (Decety et al., 1997), as well as mental rehearsal (Decety et al., 1994) (similar to what was termed "internal generation" in the architecture of chapter 4).

In Decety et al. (1994) normal subjects were asked to either passively observe move-

ments of a virtual hand grasping objects or to imagine their own hand grasping objects, presented through a virtual reality system. Their brain activity during these conditions was mapped[1]. The results demonstrated that cortical and sub-cortical motor structures were activated both during movement observation and movement imagery. It was concluded that consciously representing an action involved a pattern of cortical and subcortical activation that resembles the one observed during an intentionally executed action. It is important to note that during the observation condition, subjects were instructed to watch the movements of the virtual hand "as if it were their own hand"[2]. The importance of the observer's intentions during observation was further examined in Decety et al. (1997) where subjects observed actions with the aim of either recognising them or imitating them later. The results showed that the pattern of activation was different between the two conditions, suggesting that the motivations and intent of the observer during the demonstration determine (or at least influence) which brain structures will be activated to process the incoming stimuli. Decety et al. (1997) also examined the effect that the meaning of the observed actions has on the patterns of brain activation during observation. The results were striking: different brain structures were activated when the actions demonstrated were meaningless to the observer than those activated when the actions were known to the observer[3]. This is very interesting since it indicates that knowing or not the action demonstrated has an influence on the way this action will be processed in order to be imitated.

Mirror neurons in monkeys.

Neurophysiological experiments with macaque monkeys have revealed an important class of neurons in area F5 of the monkey's premotor cortex, which were termed "mirror neurons" (Gallese et al., 1996; di Pellegrino et al., 1992). These neurons were found to become active both when the monkey executes goal-oriented movements, and when

[1] There was also a third condition where subjects had to visually inspect presented objects without being required to carry out any action. The activity present during this condition (i.e. due to visual analysis and object recognition processes) was used as a baseline which was subtracted from the activity present in the other two conditions.

[2] This is similar to the first step taken by the behaviours in the active imitation route, i.e. internally assuming the observed state of the demonstrator.

[3] The meaningless actions were derived from the American Sign Language that the subjects were not familiar with, and the meaningful actions were pantomimes such as drawing a line, hammering a nail etc.

it observes the demonstration of similar movements executed by another monkey or a human demonstrator. A variety of mirror neurons were discovered: grasping, tearing, manipulating, and placing objects neurons, among others. Some of the neurons were active only during the demonstration while some others remained active for a while after the end of the demonstrated action. The majority of the mirror neurons are active selectively when the monkey is observing a particular type of action (e.g. grasping), and some of them are highly selective not only to the type of action, but also to the particular way that the action is executed (e.g. grasping with the index finger and the thumb). The distance of the demonstrator from the monkey does not affect the responses of the mirror neurons, and control experiments have ruled out the possibility that the neurons are active simply as a response to particular visual configurations (for example, either of the demonstrator's hand or of the monkey's own hand) since most of them are also active when the monkey executes the action in darkness. Non-biological stimuli (for example, observing a set of pliers grasping the object) do not activate the neurons.

Memory and imitation

In the approach advocated in this thesis, imitation of a movement is essentially a repetition of an earlier generative process. Substantial work in the area of working memory for movements has been conducted by Smyth and her colleagues (Smyth et al., 1988; Smyth and Pendleton, 1989). A range of experiments studied the memory span for demonstrated movements when the subject was allowed to freely observe the movements or asked to concurrently carry out a "suppression task"[4]. In the first set of studies (Smyth et al., 1988), subjects were asked to observe a series of movements either directed to spatial targets[5], or designed to achieve particular pattern of limb states (body configurations), while carrying out a "suppression task", consisting of either movements to spatial targets or body-configuration related movement. Memory span was reduced when the subject observed spatial-target oriented movements and

[4] A "secondary" task designed to test the interference between its underlying processes and the primary task that the subject is performing.

[5] In a standard "Cori blocks" task (de Renzi and Nichelli, 1975) where a set of wooden blocks is placed in front of the subject and the experimenter taps them in a particular sequence which the subject is later asked to repeat.

the suppression task was also spatial-target oriented, but was not reduced when the suppression task was body-configuration related. The reverse dissociation was also observed. Similar results were reported in subsequent experiments (Smyth and Pendleton, 1989) involving spatial target or pattern-oriented hand movements, and the same dissociations were reported in the case of well practised everyday motor tasks involving a complex interaction of the two types of movement using rowing as an example task (Woodin and Heil, 1996).

Finally, the interplay between memory and movement imitation was also studied in several other experiments. Zimmer and Engelkamp (1996) reported that the performance of subjects on free recall of a set of movements was not different in two of the experimental conditions which involved either perceiving the movement or perceiving the movements and subsequently (after the presentation of each of them) imitating them[6]. Related results were reported by Abravanel (1991) who experimented with the effects on memory of immediate vs. deferred imitation of demonstrated actions in infants, and did not find any difference between the two conditions, especially in older infants (17-20 months old). The subjects were able to encode and retain as much from perceiving the modelled acts as from imitating them. This effect was not so clear in younger infants (13-16 months old) who performed slightly better when they imitated the actions.

Observation, imagery, actual performance and imitation

Of relevance to the work presented in this thesis are also psychophysical experiments investigating the differences between observing an action, imagining an action and executing that action. Vogt (1995) performed a series of studies where subjects learned to reproduce a sequence of cyclical arm movements, either through repeatedly observing the sequence on a monitor, or through mentally or physically rehearsing the sequence. The results were very interesting since they demonstrated that observation or mental or physical rehearsal led to similar improvement in temporal consistency when the subject was later asked to reproduce the observations. Some further experiments (Vogt, 1996) with a short-term memory paradigm where subjects were allowed to observe

[6] Other experimental conditions included verbal recall and combinations of the above.

the model movement[7] only once, showed that timing imitation did not benefit from any further intermediate imitation (imaginary or physical) in the interval between the presentation of the model movement and the point were the subjects were asked to reproduce it. Related results were obtained in "mental chronometry" experiments by Decety (1996). Subjects were asked to perform a task[8] either mentally or physically. The movement times required to execute the task were very similar irrespective of the modality of execution (mental or physical). In related sets of experiments (Decety et al., 1991; Wang and Morgan, 1992; Wuyam et al., 1995), subjects were asked to mentally perform tasks that would require different physical effort[9] and found that autonomic responses (cardiac and respiratory activity) during motor imagery paralleled the autonomic responses to physically performing the task.

Brain & cognitive disorders and imitation abilities

> "In any well-made machine, one is ignorant of the working of most of the parts - the better they work, the less we are conscious of them... it is only a fault which draws our attention to the existence of a mechanism at all" . Kenneth Craik, *The nature of explanation.*

Since imitation is a complex task involving the integration of information from multiple brain systems including perception, memory and motor systems, it has been used as a reference task for identifying and assessing various brain and cognitive disorders. In particular (and most relevant to this thesis) it has been used to identify and assess the various forms of *apraxia*, a "neurological disorder of learned purposive movement skills that is not explained by deficits of elemental motor or sensory systems" (Rothi and Heilman, 1997). Apraxia usually results from brain damage (usually in the left hemisphere) and its symptoms vary, giving rise to the various forms of apraxia, which are identified through a series of tests, that involve performance of actions on verbal command, imitation of meaningful and meaningless gestures, and gesture recognition and naming. A type of apraxia of particular relevance here is *visuo-imitative apraxia*

[7] The model movements were different patterns of relative timing.

[8] Tasks included drawing a cube, writing a sentence with either hand, and walking to targets at various distances.

[9] Tasks included walking, running, walking on a treadmill, and lifting dumbbells

(Mehler, 1987). Patients suffering from this apraxia are able to perform meaningful gestures when they are described verbally, or when they are asked to imitate them after a demonstration, but are unable to imitate meaningless gestures (Goldenberg and Hagmann, 1997; Merians et al., 1997). The nature of the demonstrated act, and in particular whether the act is known or not to the imitator, appears to be very important and determines whether or not the patient will be able to imitate it. This correlates well with the brain activation data described earlier, which show that different brain areas are activated depending on the nature of the demonstrated act, and its meaning to the observer (Decety et al., 1997).

Two additional disorders are also of interest here: *autism* and *imitation behaviour*. Autism is a syndrome which includes abnormalities of social and communicative development, partially characterised by an inability to comprehend the viewpoints of other people (Baron-Cohen et al., 1993). People suffering from autism display severe deficits in imitation and pantomime tasks (Smith and Bryson, 1994), which cannot be attributed to visual recognition memory, motor initiation and basic motor coordination deficits (Rogers et al., 1996). Furthermore, autistic children show deficiencies in empathy and joint attention tasks, as well as an inability to engage in pretend play (Charman et al., 1997). On the other side of the spectrum are patients that suffer from frontal-lobe damage, and display a pathological behaviour that has been termed "imitation behaviour" (Lhermitte et al., 1986). These patients imitate the demonstrator's gesture although they were not instructed to do so, and some times even when told *not* to do so (de Renzi et al., 1996). An explicit, direct command from the doctor to the patient would stop the imitation behaviour but a simple distraction to a different subject was sufficient to see imitation reappearing, despite the patient remembering what (s)he had been told.

6.3 Explanations

Involvement of motor systems during perception

The human brain and mirror neuron activation data suggest that there is a motor system involvement during observation of movement. The explanation offered for these

data is that the motor system is activated in order to generate and internally simulate candidate behaviours, and offer predictions regarding the incoming perceptual data from the demonstrator. On a more specific note, the fact that some mirror neurons cease to be active when the demonstration is complete while others continue to be active for a while after the end of the demonstration can be explained if viewed within the composite nature of the organisation of the behaviours: more complex ones can be composed from elementary ones. Upon completion, a behaviour X ceases to be active; however, a behaviour X* which incorporates X as its initial step will continue to be active, since it is still capable of offering further predictions about the demonstrator's future states until X* completes its remaining steps. This suggests that the mirror neurons that cease to be active when the demonstrated action finishes represent that action specifically, while the other class of neurons which remain active represent sequences of actions that incorporate the demonstration as their first part.

The active route of the architecture understands an action by internally generating it. The observer does imitate the demonstrated movement internally, even when it does not do so externally. This feature of the architecture explains why physically imitating a set of demonstrated movements does not aid their later recall (Zimmer and Engelkamp, 1996), as well as why physical rehearsal of a demonstrated behaviour does not lead to any significant differences in the levels of performance improvement from mental rehearsal or mere observation (Vogt, 1995). Since observation, imagery and imitation are done using mostly the same structures (behavioural modules and forward models) the same laws should govern their operation, which explains the mental chronometry data by Decety (1996), which indicate that it takes roughly the same time to perform a task mentally or physically.

Influence of content of the demonstrated action

The human brain activation data described by Decety et al. (1997) indicate that different brain structures are activated during the observation of an action depending on whether the action is known to the observer or not. This is explained by the dual-route nature of the architecture: if the demonstrated act is known to the imitator, then the corresponding behaviour in the active imitation route will be activated. If the demon-

strated act is not known to the imitator, then the passive route will be activated in order to extract the representative postures and acquire the demonstrated behaviour. Currently, there are no brain activation data to correlate with the behaviour of the architecture for the cases where the demonstration consisted of sequences of actions, and particularly partially-known sequences.

If the passive route is destroyed, the architecture will no longer be able to imitate any novel behaviours, although, with the active route intact, behaviours that are already known will be successfully imitated. This correlates favourably with the neuropathological data for patients suffering with visuo-imitative apraxia (Mehler, 1987).

6.4 Predictions

In chapter 4, the computational studies revealed limits to what the architecture can perceive, in particular with respect to movement speeds. If the demonstration is performed at speeds that cannot be attained by the imitator, the demonstrated actions will not be understood, even if they are in the imitator's repertoire. By projecting this behaviour to that of the mirror neurons described earlier, the architecture offers a testable prediction: a mirror neuron which is active during the demonstration of an action should not be active (or possibly be less active) if the demonstration is done at speeds unattainable by the monkey. A further prediction with respect to mirror neurons has already been hinted at earlier in the explanation section. Mirror neurons that remain active for a period of time after the end of the demonstration are encoding more complex sequences that incorporate the demonstration as their first part. Further investigation through manipulation of the demonstration (adding further actions to it, while retaining the first part) should reveal the exact sequence that the neuron is encoding. Two less easily testable prediction regarding the mirror neurons are: (a) the existence of other goal directed mirror neurons and (b) the trainability of new mirror neurons. The first one predicts that there exist mirror neurons for other goal-directed actions: since perception and generation of an action is so tightly coupled, it can be expected that at least the most important actions in the monkey's repertoire (body postures that convey messages, for example threat postures, facial expressions, among others) should have mirror neurons associated with them. The second one predicts

that, since the passive route provides the active route with new behaviours after their demonstration, it should be possible to create new mirror neurons by training the monkey to imitate a demonstrated action.

6.5 Discussion

The architecture, if viewed as a model, suggests that when humans and other primates observe a movement with the intent to imitate, they "put themselves in the place of the demonstrator", and do what they would do if they were in the demonstrator's place. Understanding a demonstrated movement comes from internally generating alternatives and selecting among those, based on the quality of their predictions. But why predict? Why not wait until the demonstration has finished and classify the result? From an evolutionary perspective, the ability to predict and its adoption during observation might have prevailed since it allows the animal to act/respond to an action of a conspecific before that (potentially non-beneficial to the observer) action has been completed.

The initial step taken by the observer, of putting herself in the position of the demonstrator, seems to be important too. Autistic children who suffer from an inability to do so, as witnessed by their poor performance in empathy, joint attention and pretend play tests, are unable to imitate. Normal children observing a human experimenter demonstrating an act but failing at it[10], do imitate the intended action of the human successfully, but do not do so when they see a mechanical device trying to do the same act but failing (Meltzoff, 1995). An explanation for this could be that the children did manage to imagine themselves in the place of the demonstrator when the demonstrator was human but not when it was not of biological nature. As already mentioned earlier, mirror neurons also do not respond when the action (e.g. grasping) is done with pliers, and not by a human arm (Gallese et al., 1996).

The dual route nature of the architecture is interesting too. It was already discussed in the explanations section earlier, that damaging the passive route leads to behaviour similar to that of visuo-imitative apraxic patients. What about the reverse condition?

[10] For example, trying to pull apart a dumbbell, but failing due to finger slippage

There is currently no evidence for the reverse dissociation, i.e. having the active route destroyed while retaining the passive one intact. This condition would be hard to detect, since known behaviours can still be imitated through the passive route as being novel. However, it is important to note that, essentially, the active route maps the observed movements to the imitator's internal ones, i.e. it serves as a recognition process. Any internal representations associated with these behaviours (including symbolic ones, for example the name of the behaviour, or emotional significance, intentions or any other attributes) can be retrieved through this route[11]. There are cases reported related to a disruption to this process: Gonzalez-Rothi et al. (1986) reported two patients who could imitate demonstrated pantomimes but could not recognise (or discriminate among) them in what is termed as "pantomime agnosia".

In the experiments reported in this thesis, all behaviours that are present in the imitator's repertoire are activated in order to generate alternatives and offer predictions as to what comes next. For efficiency reasons, it is conceivable that context can be used in order to select among all the available actions the ones that are applicable or at least relevant to the current situation. Although it is still early to speculate about the exact nature of this process, experiments with humans and monkeys have shown that actions applicable to a certain context are retrieved even if no action is required on behalf of the subject. (Rizzolatti et al., 1988; Murata et al., 1997) have shown that there are neurons in the area F5 (same area with the mirror neurons) of the monkey's premotor cortex which are active during grasping movements, but are also active when the monkey views a graspable object. The interpretation favoured by the experimenters was that the responses of the F5 neurons represented the description of the presented object in motor terms, i.e. the visual features of the object are automatically translated into a potential motor action (regardless of whether the monkey intended to move or not). In humans, experiments with positron emission tomography have shown that observation of tools activated the premotor areas in the absence of any overt motor demand[12]. These data indicate that the brain might indeed be using context to reduce the amount of behaviours that will be tried out.

[11] It has been suggested (Gallese and Goldman, 1998) that the role of the mirror neurons is to facilitate the detection of the mental states of observed conspecifics by adopting their perspective.

[12] It is interesting to note that the additional task of silent tool naming did not result in any additional activation of the premotor cortex, but tool-use naming did.

Currently, a single presentation is enough for the architecture to acquire a new behaviour. It is not clear how this relates to primate behaviour but the architecture could be modified so that only frequently-occurring behaviours get acquired, or possibly the most biologically-important to the imitator. Then the passive route would essentially act as a short-term memory which would filter the behaviours letting only some of them through to the long-term memory of the active route.

Chapter 7

Conclusions

7.1 Overview of the thesis

This thesis set out to investigate movement imitation architectures, which apart from being detailed enough to be implementable on robotic systems, attempted to keep close to data that are available on monkey and human imitation. First, a computational architecture inspired by Meltzoff's Active Intermodal Matching hypothesis was designed and implemented. Its low signal requirements and its reliance on representations known to be available in the human and monkey brain makes it an attractive candidate for a model of early infant imitation mechanisms. However, it was pointed out that there are at least two lines of evidence against it being a general model of imitation. Its indifferent treatment of novel and known movements and the involvement of the motor system only during the execution phase were not in agreement with biological data on human brain activation patterns which advocate different treatment of novel and known demonstrated movements, and strong involvement of the motor systems during perception of movements.

To address these issues, a novel architecture was designed which tackled the problem from a different perspective: the imitator actively generates behaviours while the demonstration is unfolding, and selects among them based on the accuracy of the predictions they offer regarding the incoming states of the demonstrator. The motor system is actively involved during perception: the action generation systems are being used to also perform the action perception. This offers an explanation as to why the human and monkey motor systems are active both during a demonstration, and as to

why monkey mirror neurons are active both during the perception and the production of the action they encode. This also leads to testable predictions: mirror neurons encoding certain actions will be less or not active at all during the demonstration of the actions they encode, if these actions are performed at speeds unattainable by the monkey. Embodiment has been advocated to play an important role in cognition (Dautenhahn, 1997; Mataric, 1997), and this work is a demonstration that this extends to the perception side of cognition too. Perception of actions in the active route is not an abstract process, classifying events as instances of generic classes, but utilises the specific generative models that the agent has, which have been developed as a result of having to control this specific body.

However, this active architecture is unable to imitate demonstrated behaviours that it does not have in its repertoire. The final contribution of this thesis was the merging of the passive and active architectures into a dual-route model. When none of the behaviours in the imitator's repertoire accurately predicts the incoming states of the demonstrator, control is passed to the passive route which extracts the representative postures and executes them in sequence, as well as forming new behaviours with them. These new behaviours are added to the active route, and are shown to achieve good levels of confidence during the demonstration of the action they encode. Viewing imitation as a two route process correlates well with human brain activation data which indicate that different brain structures are activated during the demonstration of known and novel movements. Destroying the passive route while retaining the active one intact leads to symptoms similar to those displayed by visuo-imitative apraxia patients: while the imitator is capable of imitating known movements, (s)he cannot imitate any novel ones.

The work reported here advocates that imitation can be used to probe internal states of other agents in a social environment. Mentally putting oneself in someone's else position and generating ("imagining") potential alternatives facilitates the retrieval of any intentions, emotions or other internal attributes that are associated with them. Autistic children and adults are not good impersonators as evidenced from their performance in pretend play and joint empathy, and (possibly as a consequence) do not perform well in imitation tasks.

7.2 Future directions

There are several directions that future research continuing the work reported here can take. These include further examining the units of representation that were used by the architecture, applying the architecture to the imitation of object-related behaviours, equipping the architecture with the ability to decompose behaviours, and enabling stronger competition between the behaviours during observation. These will be discussed in the following subsections.

7.2.1 Units of representation

Both routes of the developed architecture use postures as the unit of representation: in the passive route, the demonstrator's movements are perceived and stored as sequences of postures; in the active route the confidence values of the behaviours are calculated based on the prediction error which is derived as a difference between two postural states. There are good reasons for using posture: it is always computable and it has high biological significance. However, although there is evidence that the brain has representations of the static posture available both for the visual and proproceptive modalities (and has developed associated specialised feature detectors) it is not necessary the case that they are utilised in a way similar to the one in the developed architecture. Other possibilities include more dynamic representations based on movements, for example qualitative descriptions of movement primitives of the form "move body part X in direction A", although it is not immediately clear what parametrisations would be the appropriate ones, and whether there is more biological evidence in favour of such representations than there is for postures. Of course, there isn't any theoretical reason why more that one representation shouldn't be and isn't being used.

7.2.2 Object-related behaviour

An interesting new direction for further research would be the application of such architecture on a different set of scenarios involving object-related behaviours. Imitation of picking, placing and assembling tasks would ask for additional criteria for judging the prediction accuracy of the internal behaviours. For example, comparison tests

might be focused on the distance of the demonstrator's arm from the object rather than body configurations. Predictions can also be formed at a more abstract level as well, for example, in an assembly task predictions can be made with respect to what the next state of the assembled structure will be. This would also permit a more direct comparison between this work and the robot assembly by observation work.

7.2.3 Behaviour decomposition

As it was mentioned in chapter 5, behaviours are currently treated as non-decomposable units. This means that even if parts of a behaviour match the demonstration well, the whole behaviour will be rejected as invalid. Future research should investigate methods on decomposing behaviours, and re-using parts of them if those are doing well in a subset of the demonstration. This will potentially require maintaining several independent indicators of prediction accuracy, although it is not obvious which aspects of a behaviour should have associated indicators and which ones should not.

7.2.4 Competition between behaviours

In the architecture developed the behaviours compete between each other only indirectly at the final selection stage: the one with the highest confidence value is selected. It is conceivable that competition can be initiated earlier in the process with behaviours that currently are doing well sending inhibition signals to the other behaviours. This might result in the correct behaviour being distinguished from the others much earlier in the process, but it might also result in the right behaviours being inhibited by less suitable ones because the latter perform better initially.

7.3 Epilogue

The work reported here has made an explicit attempt to bring together data from several disciplines including psychology, neurophysiology, pathology, and robotics, and construct a computational model which is general enough to encompass all these data, while being detailed enough to allow implementation on robotic platforms. Using computational and robotic models to study the properties of real neural systems is

a difficult task since, apart from terminological issues, the disciplines involved operate with different levels of descriptions. The model developed offers explanations for the biological data described, but perhaps more importantly offers predictions which can be tested back in the neurophysiological laboratory, resulting in more data which can in turn be fed back into the model. This interaction between experimentalists and modellers can drive both experimental and theoretical work forward, and makes interdisciplinary research so promising.

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Appendix A

The International Standard Semaphore Code

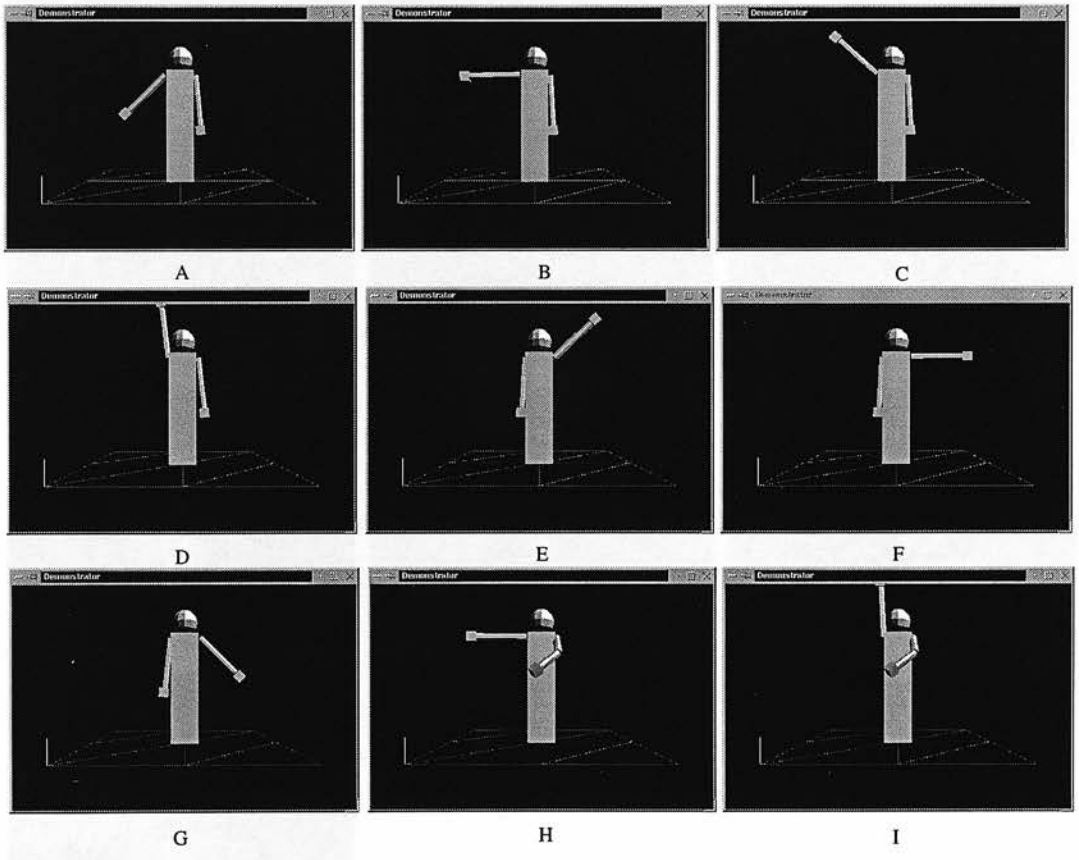

Figure A.1: Letters A-I of the ISSC

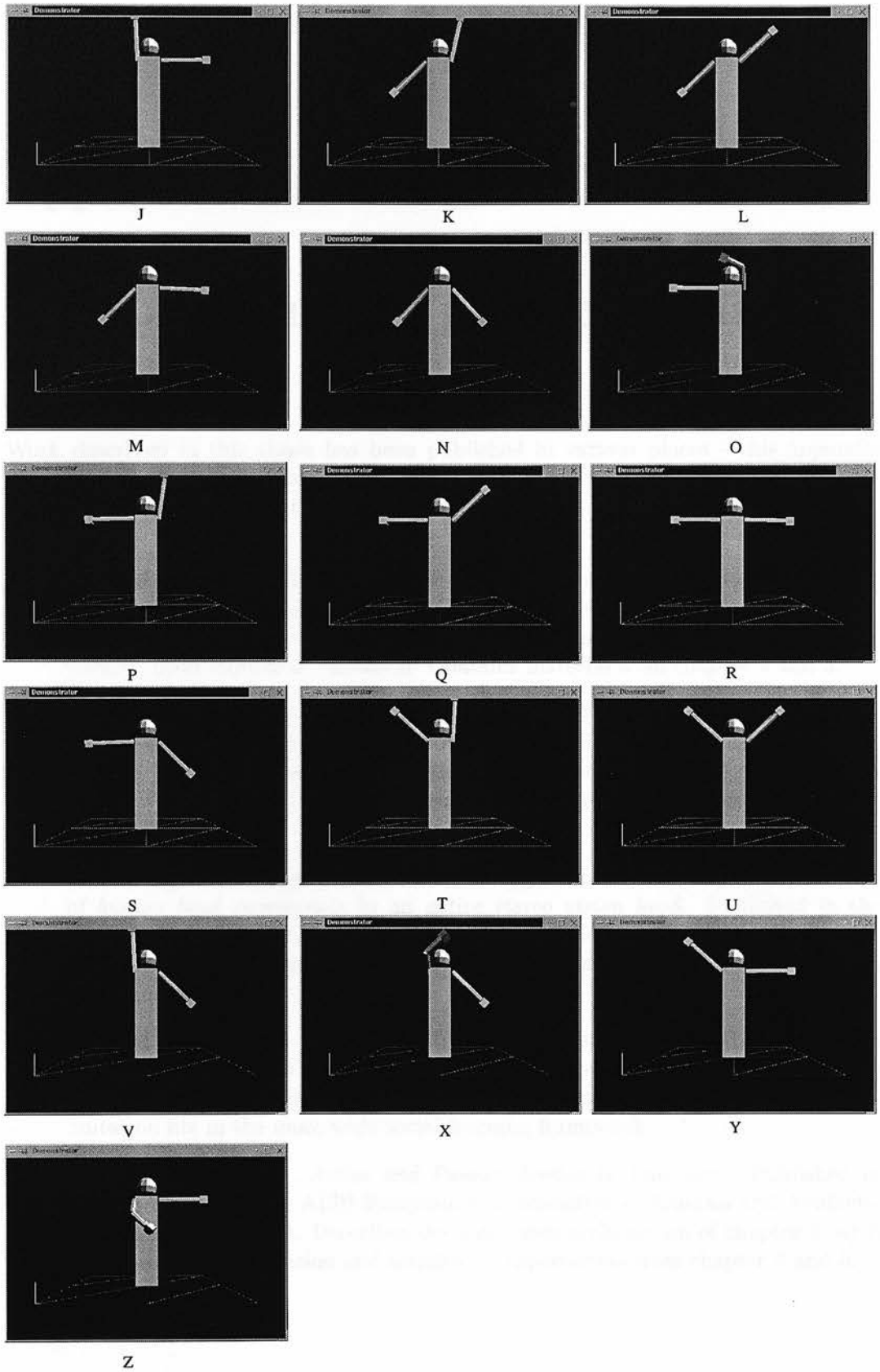

Figure A.2: Letters J-Z of the ISSC

Appendix B

List of resulting publications

Work described in this thesis has been published in various places - this appendix provides a list of these publications, together with where they appeared and what parts of this thesis they contain. Only the peer-reviewed publications are shown.

Demiris and Hayes, 1996 : *Imitative learning mechanisms in robots and humans.* Published in the Proceedings of the 5th European workshop on learning robots, Bari, Italy 1996. Describes the theoretical background and initial experiments towards head movement imitation. Contains material from chapter 2 and 3.

Klingspor, Demiris, Kaiser, 1996 : *Human-Robot-Communication and Machine Learning.* Published in the Applied Artificial Intelligence Journal, Vol. 11, pp. 719-746, 1997. The author's contribution contained material from chapter 2 and 3 on imitation of head movements, and theoretical issues on human-robot communication.

Demiris, Rougeaux, Hayes, Berthouze, Kuniyoshi, 1997 : *Deferred imitation of human head movements by an active stereo vision head.* Published in the Proceedings of the 6th IEEE international workshop on robot human communication, Sendai, Japan, 1997. Describes the deferred human head movement imitation experiments of chapter 3.

Demiris and Hayes, 97 : *Do Robots Ape?.* Published in the Proceedings of the AAAI Fall Symposium on Socially Intelligent Agents, MIT, USA, 1997. Contains theoretical material about the different levels of imitation (chapter 2) and how imitation fits in the more wide social learning framework.

Demiris and Hayes, 99 : *Active and Passive Routes to Imitation.* Published in the Proceedings of the AISB Symposium on Imitation in Animals and Artifacts, Edinburgh, April 1999. Describes the dual-route architecture of chapter 5, with single movement imitation and acquisition experiments from chapter 4 and 5.